



# **GPTMB 2024**

The First International Conference on Generative Pre-trained Transformer Models  
and Beyond

ISBN: 978-1-68558-182-4

June 30 - July 4, 2024

Porto, Portugal

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# GPTMB 2024

## Forward

The First International Conference on Generative Pre-trained Transformer Models and Beyond (GPTMB 2024), held on June 30 – July 4, 2024 focused on advanced topics on GPTM and AI/Deep Learning and target the challenges of using at large scale of GPTM-based tools. The event considers the research works and the current challenges including input data, process truthfulness, impact on existing human perception, and lessons learned from experiments.

The advances on Machine Learning (ML) and Deep Learning (DL) change the nature of summarization and text generation. GPTM (Generative Pre-trained Transformer Models) are ML models that use DL techniques to generate natural language text. As for any model, the accuracy of the output is driven by the quality of input data (sensitivity, specificity) and the processing mechanisms.

The current achievements were warmly received by industrial media corporations and scientist communities. At the same time several aspects related to trust, bias, liability, and regulations because of the high probability of spreading untrue and difficultly to be cross-checked output.

We take here the opportunity to warmly thank all the members of the GPTMB 2024 technical program committee, as well as all the reviewers. The creation of such a high quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to GPTMB 2024. We truly believe that, thanks to all these efforts, the final conference program consisted of top quality contributions.

We also thank the members of the GPTMB 2024 organizing committee for their help in handling the logistics and for their work that made this professional meeting a success.

We hope that GPTMB 2024 was a successful international forum for the exchange of ideas and results between academia and industry and to promote further progress in the area of large language models. We also hope that Porto provided a pleasant environment during the conference and everyone saved some time to enjoy the historic charm of the city.

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# An Empirical Taxonomy for Rating Trustability of LLMs

Investigating AI truthfulness even further

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**Abstract**—This paper proposes a new classification scheme for evaluating the trustworthiness and usefulness of Large Language Models (LLMs) in fact-checking and combating misinformation. Using a dataset of 1,000 questions about common myths and misconceptions from the German newspaper DIE ZEIT, the author compares LLM responses to expert-verified answers. A point-based weighting system is applied, considering factors such as the LLMs’ ability to identify uncertainty and avoid confabulation. Testing several well-known LLMs, the results suggest that some models, like GPT-4 and Claude-3, achieve “superhuman” or “expert” level performance in debunking myths. However, manual comparison of LLM reasoning with expert explanations is needed to fully validate these findings. We also examine LLM confidence scores and concludes that they do not necessarily improve answer quality or overall trustworthiness ratings. This taxonomy offers a novel approach to assessing LLM reliability in real-world applications.

**Keywords**—AI; trustability; truthfulness; trustworthiness; myths; misconceptions; urban legends; prejudice; mixture of experts; question answering; Q&A; benchmarks.

## I. INTRODUCTION

This section introduces the critical challenges of trustworthiness in Large Language Models (LLMs), setting the foundation for a detailed discussion on their potential to mislead through plausible yet inaccurate outputs. It outlines our approach to systematically address these challenges through empirical evaluation and benchmarking.

### A. LLMs and the problem with trustworthiness

The rapid development of Large Language Models (LLMs) has revolutionized natural language processing and opened up new possibilities for AI-assisted tasks. Models like GPT-3 [1], GPT-4 [2] and PaLM [3] have demonstrated remarkable capabilities in language understanding, generation, and reasoning. However, the phenomenon of hallucination, where the generated content is nonsensical or unfaithful to the provided source content, has emerged as a major flaw in these models [4] [5].

The issue of hallucination is not unique to AI systems; humans also exhibit similar behavior in the form of confabulation or the gradual addition of false information to their statements without evidence or the ability to cite sources [6] [7]. This tendency is influenced by various factors, such as personality, situation, and contextual conditions. The challenge lies in determining the point at which a person or an AI system

enters uncertain territory and should begin to limit their own statements or admit to not knowing the answer.

### B. Benchmarking flaws

Evaluating the performance of LLMs is a complex task, and existing benchmarks and metrics often struggle to keep pace with the rapid advancements in the field. Many widely used benchmarks, such as HellaSwag [8] and BIG-bench [9], have been found to contain flaws, such as linguistic errors and ambiguous questions [10] [11]. Davis [12] examines over 100 benchmarks for commonsense reasoning in AI. His conclusion is that many of them are incomplete or erroneous. Moreover, these benchmarks may not adequately reflect the real-world applications of LLMs, such as copywriting, story generation, and interactive assistance [13] [14].

Artificial Intelligence (AI) encompasses various levels, with narrow AI performing specific tasks, and Artificial General Intelligence (AGI) capable of understanding and learning across a broad range of tasks at a human-like level or even superior to humans. Generative AI, a subset of narrow AI, focuses on creating new content like text, images, or music, using models such as Large Language models (LLMs) to generate human-like outputs.

The holy grail of AI today seems to be detecting signs of AGI. It is a hype triggered by the attention economy and the scramble for investor favor. As a result, some benchmarks test abstract abilities. The criticism here is:

Nobody’s using language models to solve Sudoku and geometry problems in the real world. Instead, we want them to be brilliant copywriters, evocative storywriters, and interactive assistants. [...]

Wild amounts of money and manpower are being thrown at large language models. Is progress being measured in the right way? Edwin Chen [11]

### C. Proposition

To address the limitations of existing benchmarks and to focus on the role of LLMs as useful assistants, a new classification scheme is proposed that evaluates their performance in supporting everyday tasks and assesses their trustworthiness according to human standards. This evaluation is based on an easy-to-understand rating system that does not imply precision where it is inherently impossible.

The proposition is to evaluate LLMs using a questionnaire based on widespread everyday wisdom, urban legends, and misconceptions sourced from a German weekly newspaper’s “Stimmt’s” (German for “Right?”) section. The questions are formulated in a “Is it right that...” format, allowing for short answers of “Yes”, “No” or “Yes and No”. By comparing the LLMs’ responses to the expert-verified answers, one can assess their ability to debunk myths and provide reliable information, which is crucial in the age of disinformation and politically motivated abuse of multimedia spaces [15] [16].

The proposed questionnaire is hidden behind a paywall, reducing the likelihood of the questions and answers being included in the LLMs’ training data. This approach aims to provide a more accurate assessment of the LLMs’ performance and trustworthiness, contributing to the development of AI systems that can serve as reliable assistants in evidence-based research and fact-checking.

The primary limitations of the approach are the necessity of labor-intensive manual validation of LLM reasoning with expert explanations, and budget constraints that excluded some cutting-edge models like Google’s Gemini and Meta’s Llama 3. Additionally, the dataset from DIE ZEIT may not represent a diverse range of cultural myths, and the focus on German-language LLMs limits the generalizability of the findings. Lastly, comparing AI to human performance through anthropomorphic comparisons may oversimplify the nuanced capabilities of LLMs.

The outline of this paper is as follows: Section I addresses the trustworthiness issues in LLMs, the limitations of existing benchmarks, and introduces a new classification scheme. Section II describes the dataset, the process of creating and classifying it, and the point-based rating system, including mathematical definitions and boundary case analyses, concluding with a summary of rating categories. In the Section III, the paper discusses the importance of prompt engineering and presents the performance results of various LLMs from OpenAI, Anthropic and others, followed by a comparative analysis and examination of LLM confidence scores. Finally, Section IV suggests future research directions and improvements while summarizing the study’s findings and significance.

## II. METHODOLOGY

This section presents the methodology used to derive the new benchmark. The basis for this is a data set based on questions on widespread everyday wisdom that readers of the German weekly newspaper DIE ZEIT have asked the author of the “Stimmt’s” (German for “Right?”) section since 1997. Each week, one of these (supposed) pieces of wisdom is examined by the editors of the column and either debunked, confirmed or classified as open. The questions are asked or formulated according to the scheme “Is it right that ...”, so that the short answer to the questions can always be “Yes”, “No” or “Yes and No” (or may be open).

Based on this list of questions, a classification scheme is then developed that compares an LLM’s answer to these questions with the answers (assumed to be correct) from the ZEIT

rubric, relates them to each other and rates them with points. The total number of points across the entire questionnaire then serves as the degree of usefulness and applicability of an AI in evidence-based research and an assessment of the degree of credibility. Finally, it is argued in what way the classification scheme can be used to answer the question of whether an AI is considered to be 1. superior to the average person, 2. a (conscientious) expert or 3. even all (reasonably available) experts.

The Methodology section describes the dataset, the process of creating and classifying it, and the point-based rating system, including mathematical definitions and boundary case analyses, concluding with a summary of rating categories. In the Findings, the paper discusses the importance of prompt engineering and presents the performance results of various LLMs from OpenAI and Anthropic, followed by a comparative analysis and examination of LLM confidence scores. The Conclusion and Future Work section suggests future research directions and improvements while summarizing the study’s findings and significance. Finally, the Acknowledgements section recognizes contributions and notes the lack of specific funding, and the References section lists the bibliographical sources cited throughout the paper.

### A. The questionnaire from weekly newspaper DIE ZEIT

The questionnaire from the “Stimmt’s” section of the German weekly newspaper DIE ZEIT consists of a total of 1276 questions in the period from May 4, 1997 to November 20, 2023. More recent questions from the time after this date are not included.

The questions published in the newspaper were selected in advance by the editorial team from the questions sent in by readers and the answers were carefully and conscientiously researched in each case.

Christoph Drösser, as the main author of the column, has ensured maximum quality (by human standards) with journalistic meticulousness for decades by always resorting to recognized experts (mostly scientists or specialists, usually mentioned by name) when he could not determine or derive the answer himself on the basis of the information available to him. The high credibility of the sources is based on the institutional anchoring of the experts, their reputation or their generally recognized expertise as representatives of a specialist society or profession.

In addition to the short answer (“yes”, “no” or in part), Drösser always provides a reason and background information or explains that, according to the current state of knowledge, there is (still) no answer to the respective question. In almost all cases (78%), the question can be assigned to one of these three short answers, as they are formulated in the style “is it right that...”. Questions for which this is not the case, were removed from the data set for use as a benchmark. Similarly, questions that are very specific to a single country or region or could be perceived as offensive and potentially censored by an LLM due to restrictive usage rules were also discarded.

TABLE I  
NUMBER OF ACCEPTED QUESTIONS AND THOSE REJECTED FOR A  
VARIETY OF REASONS

	<b>Total</b>	<b>Behind paywall</b>	<b>Publicly available</b>
Accepted	1000 / 1276 (78.4%)	911 / 1167 (78.1%)	89 / 109 (81.7%)
Not a question	26 / 1276 (2.0%)	23 / 1167 (2.0%)	3 / 109 (2.8%)
Specific to a country/region	106 / 1276 (8.3%)	98 / 1167 (8.4%)	8 / 109 (7.3%)
Imprecise/unclear	81 / 1276 (6.3%)	79 / 1167 (6.8%)	2 / 109 (1.8%)
Offensive to some people	8 / 1276 (0.6%)	7 / 1167 (0.6%)	1 / 109 (0.9%)
Not answerable by yes/no	47 / 1276 (3.6%)	43 / 1167 (3.7%)	4 / 109 (3.7%)
Dependent on space of time	8 / 1276 (0.6%)	6 / 1167 (0.5%)	2 / 109 (1.8%)

Table I lists the reasons that led to exclusion. It must be emphasized that the selection was made *manually* (by a human) in the context of the present study and was not carried out automatically by a language model. Otherwise, it could not be ruled out that misinterpretations and, as a result, incorrect classification would have a negative impact on the quality of the data set. Some of the letters from readers contain not only the "Is it right..." question, but also a second, subsequent question, usually about the background, or the presumed explanation. These were also removed manually for use in the data set of the present study.

Only a small number of the answers to the questions (109 of 1276) are freely available (free of charge), the majority require a paid subscription and are therefore "hidden" behind a paywall from access by bots and crawlers. In addition, all questions and the corresponding answers are written in German, so that only an LLM that was trained on German can be used.

It is characteristic of the entire list of questions in the "Is it true" section that the short answer to each question – which is generally assumed to be correct – is "yes" (and this is true in around a third of cases, see Table II). This stems from the form in which the question is formulated and from the motivation for sending the question to the editors in the first place and ultimately being selected by Christoph Drösser. Most of the questions are difficult to answer and can be answered on the basis of facts, i.e., they are open to objective assessment. In contrast, questions about political views, personal taste, individual preferences or religious beliefs would not be published. Christoph Drösser states that he receives around 1,000 questions every year, so a large proportion are sorted out. He writes:

I still receive around 1000 questions a year, and even if many of them have already been dealt with in one of the 500 episodes, there are always some that I put on the pile of unsolved legends according to completely subjective criteria. Some stay there for quite a long time: even after ten years, I still don't

have a satisfactory answer to the question of whether dogs can smell people's fear, and I still don't know for sure how the "stainless steel soap" works, which apparently actually washes the smell of onions off your hands. That's right, I'm not infallible, I've made a lot of scientific mistakes over the years. For example, in the episode about placing eggs into cold water after boiling (the egg is no easier to peel afterwards!), I gave the egg white a pH value of 0.7 to 0.9 - it would then consist of concentrated acid and would dissolve the egg's lime shell in no time. *The judgment "true" or "not true" I have only had to revise once so far:* In issue no. 31/98, I came to the conclusion that a person could not make a glass shatter with his/her voice. In an American TV show, a rock singer with a powerful voice actually managed it, the correction was in DIE ZEIT No. 37/06.

Another important feature of the questions is that they relate to or are based on everyday wisdom, sayings or modern legends. Clichés, old wives' tales, sailors' yarns, myths or modern legends can also form the basis of reader questions. There is a presumably large amount of written evidence (including audio-visual media) for such questions, which has been incorporated into the LLMs' training data in some form, e.g., in the Common Crawl data set [17].

Figure 1 is intended to illustrate this situation in the case of a question for which there is a widespread narrative, a country saying or a generally known view in the general population, but for which, according to the expert(s), no conclusive answer or at least no answer that is provisionally assumed to be correct is actually known. The proportions in the figure are not to be understood as concrete information, but are purely indicative. In such a situation, a language model that responds to the question with the short answer "no" would be an example of a modern Pinocchio: it confabulates (or hallucinates, see Section I-A on terminology), i.e., it fills gaps in knowledge with more or less invented content. A small "spark" of truth in the assertion underlying the question is enough for a generative AI with transformer architecture to continue spinning the story due to its auto-regressive mode of operation.

In auto-regressive systems, the output is fed into the input via feedback and can thus lead to a kind of "drift": the path taken at the beginning of a conversation is continued in a self-reinforcing manner. As a result, sentences are strung together that fit well with this beginning, even if they do not fit the original question in the prompt (Yann LeCun in [18]). In this way, any connectable facts can act as the crystallization core of a narrative that takes on a life of its own.

The situation in Figure 1 serves in Section II-C as a starting point for analyzing the other possible responses, both from the expert side and from the side of the language model under investigation. Thus, an LLM's answer can be classified as parroting or "imitative falsehood" (see [19]) if it simply reflects the overwhelming database of popular opinion shown in green, despite a different classification by the experts, which



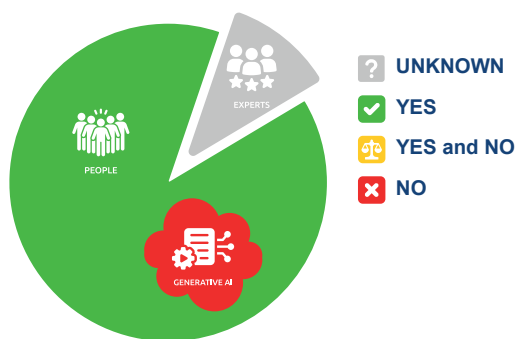


Figure 1. Example for a question in the dataset for which experts testify that the answer is unknown, whereas the AI answers “no”.

should be weighted higher by the language model in the sense of an objective consideration.

**B. Database generation and manual classification**

As described in the previous section, the 1276 questions submitted by readers of the “Is it right...” section of the weekly newspaper DIE ZEIT from previous years (period from May 4, 1997 to November 20, 2023) served as the basis for the questionnaire, from which 1000 were then manually selected for the present study (see Table I). The corresponding articles were downloaded from the newspaper’s homepage (paid access) by web scraping using the Scrapy framework [20].

A Python script was used to pre-process the articles (identify headings, dates and text corpus and remove unwanted line breaks) and write them to an SQLite database. The article was automatically split by the script into the question text and the answer from the editorial team (experts) and entered into the corresponding columns in the database. In a second step, all questions were then processed manually in order to assign them to one of the categories in table I. The aim was to be restrictive and, in case of doubt, to sort out more questions than possibly necessary.

TABLE II  
LIST OF PRESELECTED QUESTIONS WITH CLASSIFICATION (SHORT ANSWERS FROM EXPERTS)

	Total	Behind paywall	Publicly available
UNKNOWN (UNK) / NO COMMENT (NC)	58 / 1000 (5.8%)	50 / 911 (5.5%)	8 / 89 (9%)
YES (Y)	342 / 1000 (34.2%)	317 / 911 (34.8%)	25 / 89 (28.1%)
YES and NO (YN)	172 / 1000 (17.2%)	167 / 911 (18.3%)	5 / 89 (5.6%)
NO (N)	428 / 1000 (42.8%)	377 / 911 (41.4%)	51 / 89 (57.3%)

The final step was to manually work through the answers one by one and assign them to one of the four short answers in Table II. A language model could also have accomplished this work, but attempts to do so with GPT-4 were aborted for

quality reasons: Some texts do not contain the short answer in a directly recognizable way (e.g., written out as “yes”), but are indirectly included in the explanation and more or less encoded. Errors in the AI-based assignment cannot be ruled out. Another reason is that it is not possible to ensure that the answers enter into a kind of “memory” of the language model and influence the actual test run (evaluation of the LLM) and thus distort the result. According to OpenAI, GPT-4 does allow the storage of old queries to be deactivated, but doubts are justified due to the lack of transparency regarding the technical details of GPT-4.

An example of an accepted data set, which is publicly accessible free of charge on the newspaper’s website, is shown in the following translation:

**Question:** *Ticks sit on trees and wait. When an animal or human walks underneath, they feel the warmth and drop onto the victim. Right?*

**Answer:** No. Ticks don’t go that high up, and they don’t have to make any complicated flight path calculations. In fact, they usually sit in grasses and bushes. They also do not attack their victims, but are picked up “in passing”. The tick doesn’t actually mean any harm to humans, it is just after a few drops of their blood. Their bite is dangerous because they can infect us with two serious diseases: meningoencephalitis, a viral disease, and Lyme disease, which is transmitted by a bacterium. There are also legends about the best way to remove a bitten tick. For example, the tip to anaesthetize the animal with a drop of oil is wrong. The arachnid then tends to vomit in the wound and bring the pathogens into our bodies with its stomach contents. You should simply pull it out, if possible, with tweezers and without crushing it. It doesn’t matter whether you turn them, and in which direction.

© DIE ZEIT 33/2000

**C. Weighting of answers by a point based scheme**

By comparing the correct answers with the responses of the AI to be evaluated, a total of  $4 \times 4 = 16$  combinations is possible, if the AI is restricted to use the same four short answers that also apply to the answer of the ZEIT editorial team or the experts respectively. For each combination, the LLM is awarded between -4 and +4 points, corresponding to a scheme of symbols for a negative, neutral or positive ranking. This is often found in magazines with consumer tips and product tests. The overall rating then ranges from - - - to + + +.

Even though the points awarded may seem arbitrary, each and every case has been examined thoroughly, and the weight (points) has been chosen with reason. See Figure 2 for illustration. The rationale is as follows.

1) **NO COMMENT:** The LLM has no answer or cannot reply with certainty (see prompt in Section III-A), depicted in the top four pie charts in Figure 2. If this is due to the fact that the experts cannot provide an answer (i.e., the correct

answer is unknown) as shown in the leftmost pie chart, the LLM should be awarded with a positive rating. Two points are reasonable, since it is possible that the LLM just refused to answer (caused by ignorance). On the other hand, it could have targeted the experts' assessment, symbolized by the small grayish slice, which is generally what we want. Due to this unresolvable ambiguity, we cannot give the full points.

If the experts say "yes" in accordance with the common people, the whole pie chart is green, leaving no room for doubts or uncertainty. If the LLM refuses to answer in such a case, it gets a negative rating, i.e., -2 points. A slightly less negative rating is advisable, if the experts agree with the common people *in part*, shown by the yellow slice. There might be situations or conditions in which the correct answer might be "no", according to the experts. If the LLM takes this assessment as a cause for distrust, it might answer "no comment". This assumption is even more justifiable, if the experts say "no" in contrast to the ordinary people. For this reason, the LLM gets -1 point and 0 points, respectively. The weighting in all these four cases is summarized in the top row of Table III.

2) *YES*: The LLM agrees with the people and might reproduce common misconceptions, which is called "imitative falsehood" in [19] or just "parrotting". If the experts argue that the correct answer is yet unknown (grayish slice, first column), it might be that the people are right in the first place and 0 points reflect that. However, if the experts disagree and answer "no" (rightmost column), the rating should be negative (-2 points). The LLM can be attested a positive outcome, if the experts agree with the people's opinion (the two columns in the middle in Figure 2). The LLM might still reproduce the people's belief and their conception of the truth. But if this is congruent with the expert's testimony, the rating given to the LLM should be positive (+2 points for identical judgement, +1 point for in part accordance). The filter symbol in Table III represents the filtered interpretation of the expert's view on the facts.

3) *YES and NO*: The LLM is prone to confabulation, at least in part. No documents, postings or other media content (neither by the people nor the experts) support this vote, therefore the rating is negative. The situation is depicted by the first two pie charts in the third row of Figure 2 and the weights are given in Table III, with -3 points for the worst circumstances (people and experts fully agree, and the LLM makes up some reasoning for the contrary). The crosshairs in the illustration symbolizes the origin of the data basis for the outcome the LLM produces. If it is the experts' point of view (at least in part) as shown in the right, the weights should be positive, with a fully congruent assessment representing the best case (3 points) and an overlapping situation for the second best judgement. The latter is slightly less rewarded, because the LLM might rely on a mixture of sources i.e., from experts (good) and common people (inferior choice) without proper differentiation of the sources' associated competence or reputation.

4) *NO*: The last row in Figure 2 and in Table III represents those situations with the most decisive rating. In the first two pie charts, the LLM is shown as source of confabulation, which obviously generates some sort of reasoning to come to the conclusion "no" (despite opposing evidence). This is even worse if compared to the row above, since "no" is definitive and there is no reason (data basis) for this. One could argue that the grayish slice might introduce some sort of disbelief or doubt in the people's position, represented by the green part of the pie chart. In this way, the experts' judgement would act as a root for the LLM's hallucination (to use this term for the adversely created content) and the rating is therefore -3 and not the lowest possible score. However, if the whole pie chart is green, there is absolutely no justification for the LLM to come up with a completely different result, so -4 points is reasonable. On the other hand, if the LLM fully agrees with the experts in judging "no" despite the fact that an overwhelming majority of available source (i.e., the people's point of view/opinion), the LLM has successfully been able to distinguish between those two sources and correctly "decided" to only follow the vote of the experts. Acting this way is clearly desirable and should therefore be awarded with the overall highest number of points, which is +4.

It should be noted that the reasoning of the LLM, i.e., the explanation the LLM is giving in terms of spelled out text, has been ignored for the test run described in this paper (see Section III). Of course, it would be possible and even recommended to compare the LLM's explanation in each and every case with the explanation of the experts, given the fact that the latter serves as a reference and their reasoning is readily available. However, this task is laborious and must be done manually, something that was not possible without additional workforce.

#### D. Formal definitions

Matrix  $\mathbf{N}$  gives the number of answers for all combinations in Figure 1 and Table I, e.g.,  $n_{N,N}$  denotes the number of questions that were answered with "no" by both, the LLM and the experts.

$$\mathbf{N} = \begin{pmatrix} n_{NC,UNK} & n_{NC,Y} & \dots \\ \vdots & \ddots & \\ n_{N,UNK} & & n_{N,N} \end{pmatrix}$$

Matrix  $\mathbf{P}$  represents the individual points from Table I.

$$\mathbf{P} = \begin{pmatrix} +2 & -2 & -1 & 0 \\ 0 & +2 & +1 & -2 \\ -2 & -3 & +3 & +2 \\ -3 & -4 & +1 & +4 \end{pmatrix} \quad (1)$$

The total number of points of a certain LLM is given by summing up for each category in matrix  $\mathbf{P}$  as many points as the number of answers given by the LLM in that category. For instance,  $p_{N,N}n_{N,N}$  is the number of points gathered by the LLM for category "NO/NO", i.e., matching answers. This category is rated highest among all, since the LLM agrees to the experts' opinion despite the contrary opinion by the people.

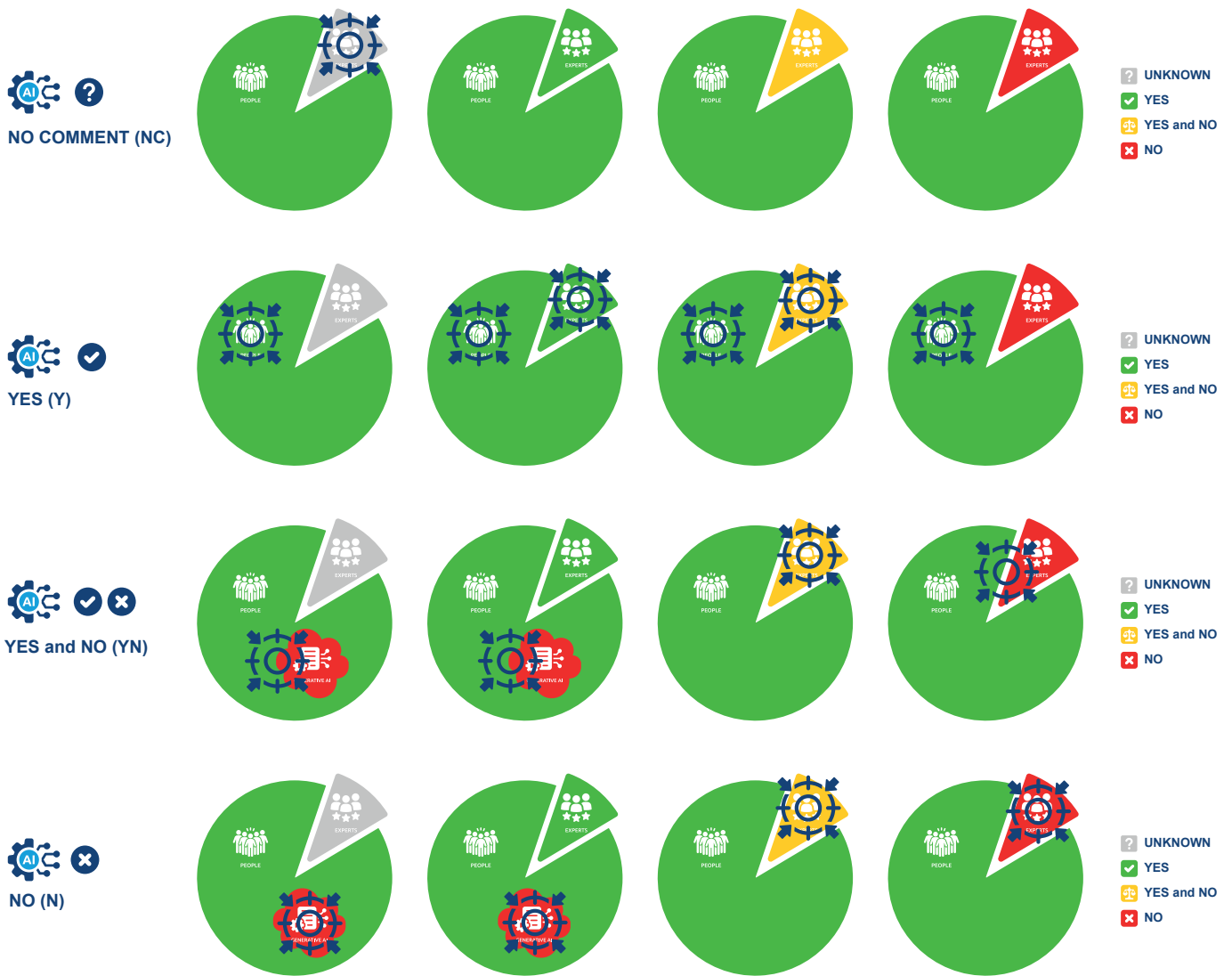
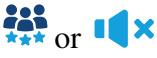







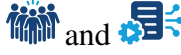


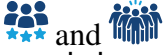






Figure 2. All possible combinations of answers given by the experts (redacted expert testimonies) in columns and answers from AI/LLM in the rows. The pie chart represents the amount of available data acting as source for a certain judgement.

TABLE III  
TAXONOMY

LLM \ Experts	UNKNOWN (UNK)	YES (Y)	YES and NO (YN)	NO (N)
NO COMMENT (NC)	 ++	 --	 -	 0
YES (Y)	 0	 ++	 +	 --
YES and NO (YN)	 --	 --	 +++	 ++
NO (N)	 --	 --	 +	 +++

The overall number of points in all categories is given by summing up across all columns and rows (Frobenius inner product):

$$\sum_{i=1}^4 \sum_{j=1}^4 p_{ij} n_{ij} = \text{tr}(\mathbf{P}^T, \mathbf{N}) = \langle \mathbf{P}, \mathbf{N} \rangle_F$$

The expression above is then normalized by the total number of questions used, i.e., the sum of all elements in matrix  $\mathbf{N}$ , giving the final rating  $R$

$$R = \langle \mathbf{P}, \mathbf{N} \rangle_F / \sum_{i=1}^4 \sum_{j=1}^4 n_{ij} \quad (2)$$

with  $R$  ranging roughly between  $-3, \dots, +3$  for typical scenarios.  $R$  should not be misunderstood as a fine-grain rating on the basis of a perfect, absolute scale. Although the result can be used as a relative measure to compare different LLMs, using more than two digits after the decimal point would falsely imply a level of precision that does not exist. This is due to the fact that a Q&A dataset inherently offers a wide scope of interpretation as all question answering tasks in natural language do. A simplified, stripped-down version of an *absolute* scale is given in Table IV and derived in the following sections, but it is very limited (confined to integers) and should be interpreted with care.

From the fact that the number of questions attributed by the experts to categories UNK, Y, YN and N as given in Table II differs between rows, it follows that the points that can be earned in each case also varies. However, this does not introduce a bias of some sort, as long as all questions are always used for the evaluation of an LLM: The expression already takes into account the non-uniform distribution of the questions with respect to the experts' answer by a scaling factor that reflects the ratio between the number of questions in a category and the total number of questions. As an example, let  $c_2 = c_Y = 317$  be the number of questions (behind paywall) with answer "yes" given by the experts as shown in the second row of Table II. The total rating for this category "yes" is then given by

$$\sum_{i=0}^4 p_{i,Y} \frac{n_{i,Y}}{c_Y} \times c_Y / \sum_{j=0}^4 c_j \quad (3)$$

with  $c_Y / (c_1 + \dots + c_4) = c_Y / (c_{\text{UNK}} + c_Y + c_{\text{YN}} + c_N) = 317 / (50 + 317 + 167 + 377)$  being the contribution ratio (amount of "yes" answers in relation to all) and  $n_{i,Y} / c_Y$  being the "actual earning ratio" ranging from 0% to 100% depending on how many questions were counted for the respective answer of the LLM. Clearly, the sum of all earning ratios for category "yes" corresponds to the second column in Table III and equals 100%. Moreover, the sum of all questions  $c_1 + \dots + c_4$  as in the second row of Table II equals the sum of all elements in matrix  $\mathbf{N}$ , if no questions from the dataset (behind paywall) are left out in the evaluation of an LLM. In other words:

$$\sum_{j=0}^4 c_j = \sum_{i=1}^4 \sum_{j=1}^4 n_{ij}$$

This way, the sum of Equation 3 for all columns in Table III yields the simplified expression for  $R$  in Equation 2.

### E. Boundary Cases

In the following, canonical boundary cases will be studied. If anthropomorphizing of AI can be tolerated for the sake of illustration and to evaluate its human-like capabilities, one can easily come up with such an enumeration of specific cases.

1) *Agnosticism*: If the LLM answers "no comment" to all (non-public) questions, it refuses to make statements and in a way, the AI can be compared to an agnostic human being. A cautious person can be thought of as someone who rather chooses to not answer in cases of doubt, than answering falsely or untruthfully. In the real world, most persons would supposedly at least answer some of the questions in the Q&A dataset, but it should be kept in mind that in this particular case, the questions are all rather hard to answer and the implied answer "yes" is obviously in doubt. Otherwise they would not have been directed to the editorial journalist of the DIE ZEIT weekly newspaper.

For this reason, the assumption is that the LLM gives answer "NC" to *all* questions, which can be expressed by vector

$$\mathbf{n}_1^{\text{NC}} = (50, 317, 167, 377)^T$$

representing the first row in Table III and earning a many points as vector

$$\mathbf{p}_1 = (+2, -2, -1, 0)^T$$

indicates, given in the first row of Equation 1. The rating is then given by

$$R^{\text{NC}} = \langle \mathbf{p}_1, \mathbf{n}_1^{\text{NC}} \rangle_F / \sum_{j=1}^4 n_{1j} \approx -0.8 \Rightarrow \boxed{R^{\text{NC}} \approx -}$$

2) *Average human / public opinion*: All questions from the questionnaire (publicly accessible and behind paywall) under the assumption that the answer is always "yes" ("it is true"), i.e., the level of knowledge / opinion of any person representative of the general population (average person without expert knowledge and editorial research work). The AI can be compared to a person with a bona fide attitude.

$$\mathbf{n}_2^{\text{Y}} = (58, 342, 172, 482)^T$$

This is the implicit answer to all questions (including the publicly available ones), therefore, the whole dataset can be included. The points are given by

$$\mathbf{p}_2 = (0, +2, +1, -2)^T$$

leading to a rating of

$$R^{\text{Y}} = \langle \mathbf{p}_2, \mathbf{n}_2^{\text{Y}} \rangle_F / \sum_{j=1}^4 n_{2j} = \frac{0}{1000} \Rightarrow \boxed{R^{\text{Y}} = \mathbf{0}}$$

3) *Undecisiveness and relativism*: Individuals who cannot commit themselves and do not believe in any fixed truth (relativism). They believe that everything is a matter of interpretation and that the truth of statements always depends on the point of view. This is different from the situation in Section II-E1 in terms of quality: The LLM is assumed to give the answer “yes and no” to all (non-public) questions, which actually is a distinct statement and not just abstention.

$$\mathbf{n}_3^{\text{YN}} = (50, 317, 167, 377)^T$$

with

$$\mathbf{p}_3 = (-2, -3, +3, +2)^T$$

leads to

$$R^{\text{YN}} = \frac{204}{911} \approx 0.2 \Rightarrow \boxed{R^{\text{YN}} \approx \mathbf{0}}$$

4) *Negativism*: An individual who has a negative attitude towards public opinion and basically assumes that the general public is wrong. The number of answers is again given by a single row in Table III (last row) and equals  $\mathbf{n}_4^{\text{N}} = (50, 317, 167, 377)^T$  with  $\mathbf{p}_4 = (-3, -4, 0, +4)^T$ . This leads to a rating of

$$R^{\text{N}} = \frac{257}{911} \approx 0.3 \Rightarrow \boxed{R^{\text{N}} \approx \mathbf{0}}$$

5) *Scepticism towards experts and superstition*: An individual who distrusts expert opinion and basically assumes that the elites are either wrong and, where the experts cannot make any statements because the correct answer to a question is unknown (UNK), assumes that everyday wisdom (popular belief) is correct. If the experts answer with “yes and no”, i.e., a differentiated answer is necessary, they are also following popular beliefs. In this case the answers are not represented by a single row in Table III, but distributed among the different categories:

$$\mathbf{N}^{\text{Sceptic}} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 50 & 0 & 167 & 377 \\ 0 & 0 & 0 & 0 \\ 0 & 317 & 0 & 0 \end{pmatrix}$$

The total sum of answers is again 911 for the non-public set of questions (see Table II) and the points are given by the respective cells (non-zero in  $\mathbf{N}^{\text{Sceptic}}$ ) in Equation 1.

$$R^{\text{Sceptic}} = \frac{-1855}{911} \approx -2.1 \Rightarrow \boxed{R^{\text{Sceptic}} \approx --}$$

6) *Conspiracy theories*: An individual who distrusts expert opinion and basically assumes that the elites are either wrong and, where the experts cannot make any statements because the correct answer to a question is unknown (UNK), assumes that the opinion of the general public “yes” must be wrong. If the experts answer with “yes and no”, i.e., a differentiated answer is necessary, they refuse to make a statement. Such individuals tend to confabulate and/or give attention and possibly credence to conspiracy theories.

$$\mathbf{N}^{\text{Conspiracy}} = \begin{pmatrix} 0 & 0 & 167 & 0 \\ 0 & 0 & 0 & 377 \\ 0 & 0 & 0 & 0 \\ 50 & 317 & 0 & 0 \end{pmatrix}$$

$$R^{\text{Conspiracy}} = \frac{-2339}{911} \approx -2.6 \Rightarrow \boxed{R^{\text{Conspiracy}} \approx ---}$$

7) *Above average human level / usefulness*: There are several scenarios in which the rating can end up with a significant positive value. A rating of  $\approx 1.06$  or + in shorthand notation can be achieved for the following distribution of answers:

$$\mathbf{N}^{\text{useful}} = \begin{pmatrix} 0 & 0 & 0 & 377 \\ 50 & 317 & 83 & 0 \\ 0 & 0 & 84 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$R^{\text{useful}} = \frac{969}{911} \approx 1.06 \Rightarrow \boxed{R^{\text{useful}} \approx +}$$

In such a scenario the correct answer “no” gets answered by “no comment”, expressing the obvious discrepancy between the judgement of the few (the experts) and the many, i.e., the public opinion (believing in “yes”). If the experts do not know the correct answer (“unknown”), the public opinion “yes” is taken as self-evident best choice. The correct answer “yes and no” is split into half in this scenario, meaning that “yes and no” is interpreted as a rather broad and vague answer which can be attributed to “yes” in some cases (here 50%) due to the bias introduced by the public opinion (saying “yes”). If there is a perfect match for this answer, the rating is slightly higher (1.25). This scenario and the respective rating can be labelled “useful”, since an LLM that can distinguish between the expert’s point of view and the public opinion in case of contradictory answers (people’s myth says “yes”, expert says “no”) can be used to investigate such cases further. The answer “no comment” can even be considered as better than any other (except “no”), because it expresses the LLMs limitation in answering truthful.

8) *Expert level*: In this scenario the LLM agrees with the people in the street for all questions to which the correct answer is not known (experts say “unknown”); therefore, the short answer is “yes”. For all questions with the correct answer “no” the LLM responds with “yes and no”, which can be interpreted as a mixture of the public opinion of the people in the street (“yes”) and the experts’ point of view (“no”). A perfect LLM should ignore the people’s opinion and just rely on the experts’ testimony (or draw its own conclusion based on learned principles), but in this scenario the LLM chooses to make a Solomonic judgement (like king Solomon in the Bible). For the remaining other two categories of correct answers, the LLM responds identical to the experts. Such scenario is described by the following matrix:

$$\mathbf{N}^{\text{Expert}} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 50 & 317 & 0 & 0 \\ 0 & 0 & 167 & 377 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$R^{\text{Expert}} = \frac{1889}{911} \approx 2.07 \Rightarrow \boxed{R^{\text{Expert}} \approx ++}$$

This level can be called “expert level”, since the LLM predominantly responds the same way as the real experts do. The

difference to the scenario described by  $N^{\text{useful}}$  above is that the LLM actually does have a distinct answer to all questions and is not reluctant to take a stand (just as experts tend to have a rigorous position on almost any topic). Therefore, no answers are given in the first row representing “no comment”. This might seem disadvantageous, but it could also be an example of good practice: For all open questions (“unknown”) the wisdom of the crowd is the preferred choice until it is known better, according to the principle “all knowledge is provisional”.

9) *Theoretical limit (perfectly identical answers)*: If the LLM always answers all (non-public) questions identically as the experts and is therefore as good as all the experts put together. However, this value will not be achieved in reality, as there are always a few questions to which the LLM answers differently in a realistic scenario. With such a high result, it is reasonable to assume that the LLM had access to the questionnaire (leaked to the public) and that the expert statements were either incorporated into the training data or were looked up (“open book”, refer to Section IV-A).

$$N^{\text{Perfect}} = \begin{pmatrix} 50 & 0 & 0 & 0 \\ 0 & 317 & 0 & 0 \\ 0 & 0 & 167 & 0 \\ 0 & 0 & 0 & 377 \end{pmatrix}$$

$$R^{\text{Perfect}} = \frac{2743}{911} \approx 3.0 \Rightarrow R^{\text{Perfect}} \approx \boxed{+++}$$

#### F. Overall rating categories

Summarizing all of the previous findings in Table IV, one can assess what performance LLMs can achieve in human terms. This comparison is the result of explicit anthropomorphism and may be regarded as non-permissible. However, as indicated before, it is not claimed to represent a fine-grain scale with sub-decimal-digit precision. For this reason, only integer values for  $R$  should serve as a reference, represented by the plus or minus symbolization, with **O** being the baseline. Every LLM that achieves a rating of  $R \gg 0$  is better than the ordinary people with  $+$  representing the level of true usefulness.

TABLE IV  
RATING CATEGORIES

Rating	Assessment
---	Conspiracy and lying press theorist
--	Sceptic and/or superstitious individual
-	Agnostic individual (person reluctant to express opinion)
<b>O</b>	Average human level (people’s / public opinion)
+	Above average human level / usefulness
++	Expert level
+++	<i>Theoretical</i> (Q&A leaked, used for training / data retrieval)

The comparative approach in Table IV provides a simplified yet insightful perspective on the relative performance of LLMs. Consequently, it offers a pragmatic way to gauge their effectiveness in real-world applications, while acknowledging the limitations inherent in such anthropomorphic assessments.

### III. FINDINGS

This section presents the ratings of different well-known large language models and a comparison. They have been chosen due to their availability, expected performance and their command of the German language. Some recently released models could not be included, even though they are supposed to be on the cutting edge of the development. For instance, Google’s Gemini family as well as Meta’s Llama 3 could not take part for this very reason. Moreover, the study was not publicly funded, so the costs for running each model posed a hard limit on the coverage of models. Table V shows all models used in this survey.

TABLE V  
LLMs USED FOR A COMPARATIVE STUDY IN THIS PAPER.

Vendor	Model Identifier
OpenAI	gpt-3.5-turbo-0125
OpenAI	gpt-4-turbo-2024-04-09
OpenAI	gpt-4o-2024-05-13
Anthropic	claude-3-haiku-20240307
Anthropic	claude-3-sonnet-20240229
Anthropic	claude-3-opus-20240229
Mistral AI	Mixtral-8x7B-Instruct-v0.1
Aleph Alpha	luminous-base-control-20240215
Aleph Alpha	luminous-extended-control-20240215
Aleph Alpha	luminous-supreme-control-20240215

The selected models provide a comprehensive overview of the current capabilities in the field. This analysis highlights both the strengths and the limitations of the included models, offering valuable insights into their comparative performance.

#### A. Prompt engineering

Prompt engineering has become some sort of discipline of its own [21]. Proper formulation of the task the LLM should perform is important to yield the desired results.

The prompt was used to describe the scenario and the role the LLM was expected to take. The prompt was therefore separated into a first part with the instruction on how to answer and a second part with the actual question. Such structuring is considered to be good practice and generally improves the outcome. Improved results could be expected, if instead of this “zero-shot learning” approach, at least a single example of the answer to be generated would be presented to the LLM (“few-shot learning”) as part of the input prompt [1].

The following paragraph represents the input prompt used:

You are a helpful assistant and answer questions about the real world. Interpret each question literally and research each answer carefully without falling for common myths. Only give the short answer "yes" or "no" if you are sure that this is the correct answer. If you are sure that the answer to the question is both "yes" and "no", give the short answer "yes and no". If you cannot answer the question

with certainty, the short answer will be "no comment". Give a confidence score and justify your answer (rationale). Always answer in JSON format (without using Markdown code blocks or other formatting). The JSON schema should contain:

```
{"short_answer": string,
  "confidence_score": number (0-1),
  "rationale": string}
```

Question: ...

The prompt demands the LLM to output JSON data in order to easily evaluate its answers and to compare them with the expert's answer in the SQLite database. However, the "weaker" models did not follow this instruction: Aleph Alpha's "base" model only responded in plain text ("yes" or "no"), omitting the rationale in most cases and the confidence score for all queries. The "extended" and "supreme" models did output JSON in the majority of cases, but with erroneous string formatting (missing quotation marks). For a number of queries, the answer was plain text in case of the "extended" model. The Mixtral-8x7B-Instruct model was given the prompt above without JSON part ("Always answer in JSON format..." omitted), since it ignored this part anyway. Moreover, the model left out the rationale in many cases or it was not useful (e.g., containing only repetitions of the short answer) and the confidence score was always 1.0.

After all, the three OpenAI models and the three models of Anthropic did in fact respond accordingly, using the JSON format perfectly in case of OpenAI. Their models are advertised to be able to output JSON compatible responses, if an additional parameter is used in the query (`response_format={"type": "json_object"}`), so this behavior was expected. The Claude 3 family does not provide such a parameter, but the output was indeed in JSON format. The only flaw was the missing escape sequence `\` for quotation marks inside of the strings representing the rationale. They had to be escaped afterwards to yield proper JSON.

As pointed out before (see Section II-C), the explanation of the LLM as demanded in step 2 of the prompt was not used in the context of the present paper. However, instead of discarding it, it could be incorporated into the weighting scheme (points) in Table III, serving as justification for awarding the respective points in each and every actual case and to differentiate in the scheme even further.

### B. OpenAI's GPT-Series

OpenAI is generally regarded as one of the leading companies in the field of generative AI and is known for its GPT series of LLMs. Figure 3 shows the results for two runs each with GPT-3.5-Turbo, GPT-4-Turbo and the newest GPT-4o model. The difference between the two runs serves as an indicator for the variability in the rating achieved, although a multitude of runs should be performed to get real statistics.

This was not possible due to budgetary limitations. However, as can be seen from the two runs, the rating varies slightly. It should be noted that the input to the models was exactly the same for the two runs, including the parameters used in the query. OpenAI introduced a seed parameter that can be used to produce reproducible output in the future. According to the documentation, this feature cannot be used reliably as of now.

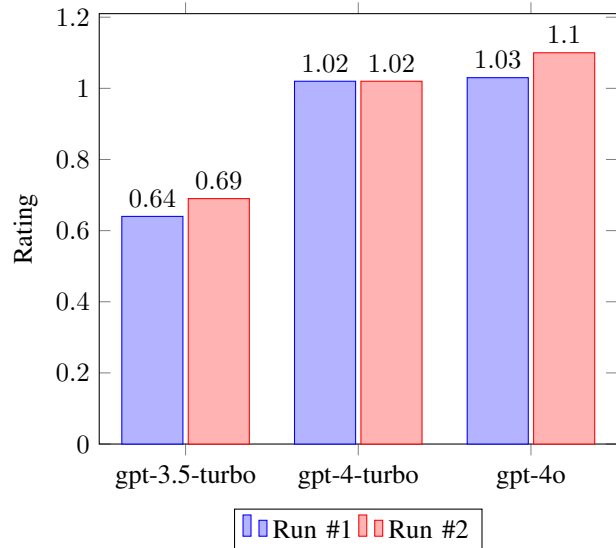


Figure 3. Results for OpenAI GPT-Series.

The results are impressive in terms of the model's capability to debunk common myths and can be classified as "superhuman level" or "expert level" in case of GPT-4-Turbo and GPT-4o. Both achieve a rating of +, provided that each rationale can be accepted for all the correct short answers given. This can only be certified eventually in a time consuming manual process by comparing each rationale with the corresponding explanation of the experts in the DIE ZEIT database. For all divergent reasoning, the short answer should be downgraded to a certain degree, which is yet to be determined.

### C. Anthropic's Claude 3

Anthropic AI announced the "Claude 3" model family in March 2024 [22]. The rating results in Figure 4 for two different runs suggest that the reproducibility is quite good, with the best model Claude-3-Opus beating OpenAI's "frontier model" GPT-4o. The improvements from the cheapest (in terms of costs per query) model to the most expensive are significant and coincide with the advertised curve in performance.

### D. Comparison

In this section, we present a comparative analysis of the ratings for LLMs from various vendors, expanding upon the vendor-specific results discussed previously. Figure 5 shows the best case results (for those with two runs) of all LLMs tested in this survey. For each vendor except Mistral's three sizes of models have been studied, with "base model" being the smallest (and cheapest) and "frontier model" being the

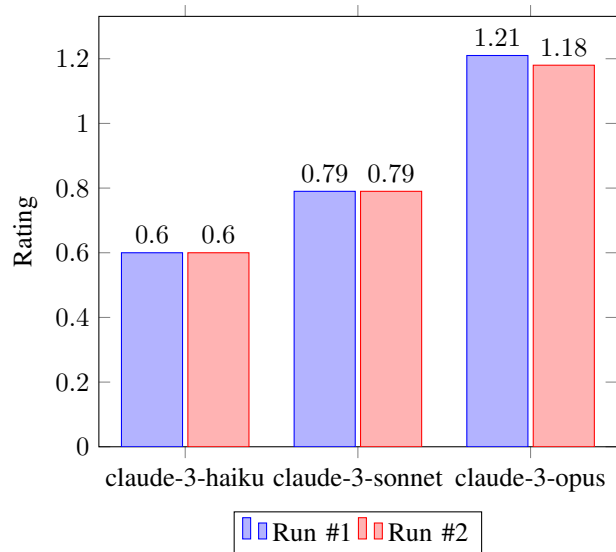


Figure 4. Results for Anthropic’s Claude 3.

most advanced (most expensive). “Standard model” denotes the established model. This categorization is not based on a consensus between vendors, but serves as a descriptive means in the context of this paper. For all ratings above the red line indicated by +, one can attest better than average human performance, with “human” representing the ordinary people in the street. Such LLMs can be classified as useful in the sense that they in part reach an expert’s level, surpassing normal persons on average. The expert in this context is not all knowing, but better in certain fields of expertise than a layperson who tends to fall for common myths or believes in the public opinion in lack of better knowledge. The red lines may imply a sharp threshold, but it should rather be interpreted as a threshold range.

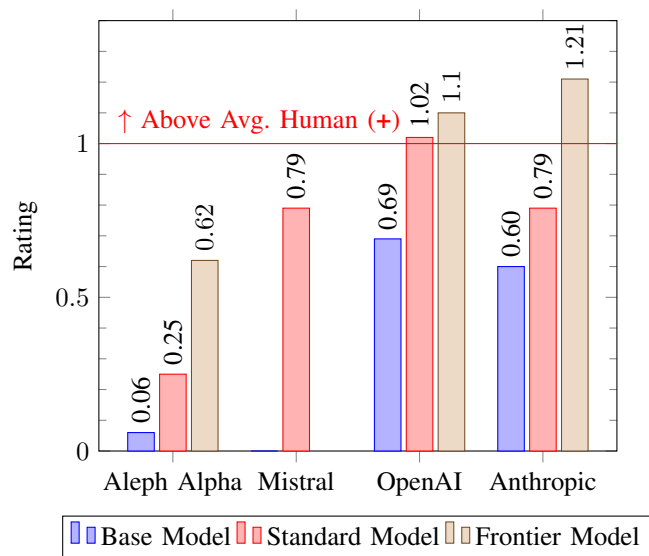


Figure 5. Comparison of the best case rating for all tested models.

The analysis in Figure 5 in underscores the potential of advanced LLMs to perform at or above human expert levels in specific domains, highlighting their practical applications and limitations.

E. Confidence Score

With the exception of the “Mixtral-8x7B-Instruct” and the “luminous-base-control” models, the LLMs responded with a confidence score, besides answering the question itself. This was demanded in the prompt, even though it can be considered redundant with respect to the phrase “...if you are sure...” as a prerequisite for giving one of the three distinct answers “yes”, “yes and no” or “no”. If unsure, the LLMs were instructed to output “no comment”. For this reason one would expect the LLMs to only return a confidence score of 1.0 (for 100%) in case of a distinct answer and a lower confidence score if the answer is “no comment”. However, the interpretation of the confidence score must be different: Analysis shows that the LLMs also gave short answers other than “no comment” for much lower confidence scores. Most of the distinct short answers were associated with a confidence score well above the 70% level, but a few were between 50% and 70% and a single one below 50%: When the model GPT-4o was run with a “temperature” higher than the obvious value of 0 (the most focused and deterministic setting), the model was more confident about its truthfulness, in spite of a low confidence score. In this run the parameter “temperature” was set to 1.0 leading to more randomness in the output as OpenAI’s documentation puts it. GPT-4o answered “yes” in this single case, with a confidence score as low as 30%, which clearly contradicts the instruction in the prompt. This may be regarded as singular fault or runaway value, owing to the higher temperature setting.

Figure 6 gives an impression of the distribution of the confidence scores for the best case runs of all models which returned a confidence score. The granularity of the score was always constricted by the LLMs to the values given in the legend of the figure, i.e., steps of 5% to differentiate. Scores of 98% and 99% were only given by the two leading edge LLMs GPT-4-Turbo and Claude-3-Opus. The other models responded with the coarser graduation of 5%.

The plot shows no clear pattern, except for increasing confidence for larger models within a family of models: Claude-3 associates a higher number of answers with a confidence score of 90% and 95%, when moving from the base model “Haiku” to the next higher model “Sonnet”, and then to the most advanced model “Opus”. For the GPT family this is not true, since GPT-3.5-Turbo outputs most answers with a confidence score of 80% and above, whereas GPT-4-Turbo and GPT-4o have a significant amount of answers with confidence score of 70% and 75% (some even below).

When taking into account the varying levels of confidence in Figure 6 and their associated answers, the question arises: is the LLM capable of correctly distinguishing between “sure” and “not sure” as demanded by the prompt (see Section III-A)?



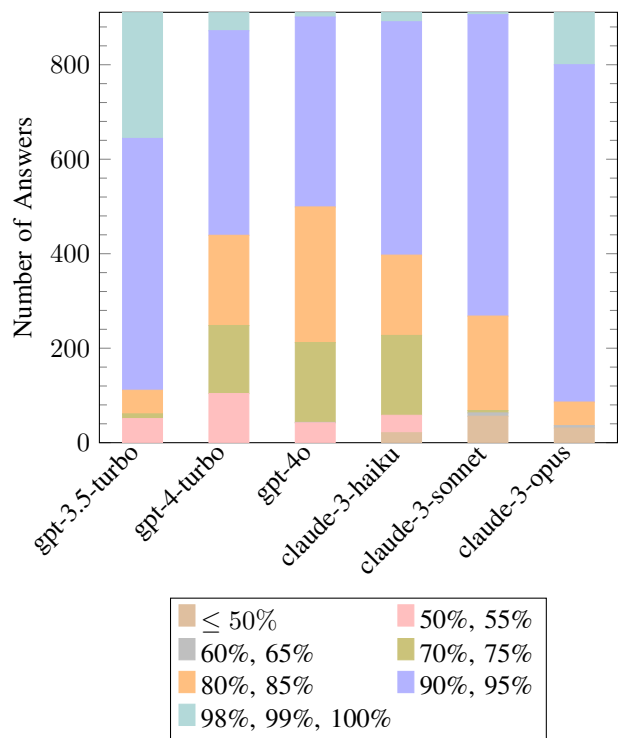


Figure 6. Distribution of confidence scores.

In this context “correctly” means truthful and based on facts and figures underlying the LLM’s training data.

Figure 7 shows the declining rating of the LLMs when plotting the rating against the confidence score as reported by the LLM. When the LLM gave an answer “yes”, “yes and no” or “no” with a confidence score below the given value on the horizontal axis, the answer was interpreted as “no comment”. This way the bar is raised step by step and the scores on the rightmost side of the plot represent the most rigorous situation. With such a high expectation regarding confidence, the score drops significantly for all models, reaching a negative level for the second best model of Aleph Alpha (“luminous-extended-control”). The overall conclusion to be drawn from this plot is that taking the confidence score into account does not improve the quality of the answers and thus the rating or vice versa.

#### IV. CONCLUSION AND FUTURE WORK

The following section examines the steps that need to be taken to advance the concept presented and summarizes the findings of this study.

##### A. Next Steps

One of the most obvious steps to be taken next is a comprehensive evaluation of all the other major LLMs like Meta’s Llama 3, Google’s Gemini or Grok of xAI on the basis of the rating scheme presented in this paper (provided they have a command of German). Currently exist 28 publicly available and just as many closed source models, having a size larger than 10B [23]. Besides these well-known models, specialized and optimized versions also seem worthwhile,

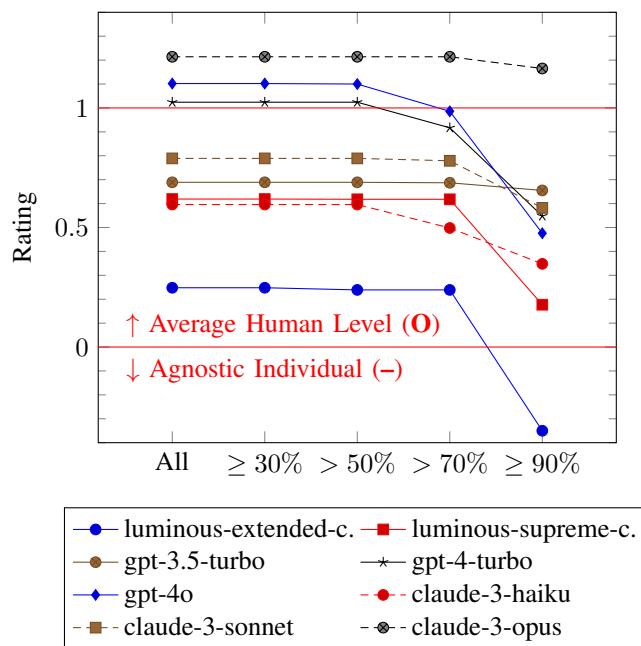


Figure 7. Rating versus confidence score.

especially the ones with a Mixture-of-Experts (MoE) architecture. This approach might yield better results if the “experts” are mixed in such a way that it resembles the combination of those experts that were consulted by Christoph Drösser, the author of the ZEIT rubric. His approach also represents a “mixture of experts” in a very literal sense.

Another field of study is the influence of the prompting on the results. The LLMs were instructed to take the role of an assistant for the present survey. Do the results get better if the LLMs are given the role of an expert instead? Or, on the other hand, do they even get worse, because in media, experts are always self-confident and mostly have a distinct opinion, whereas the answer “no comment” is very seldom. Real experts are usually asked for their opinion if it is assumed that they actually have something valuable to say and this might introduce a bias in the training data of the LLMs.

The results might also benefit from techniques like Chain-of-Thought (COT) prompting. One attempt in this way could be to ask for the reasoning first, and then afterwards in a second step to ask for the short answer. A modification of the COT-technique has been published in [24] and was titled “Chain-of-Verification Reduces Hallucination in Large Language Models”. This approach would be worthwhile to investigate.

The concept of “open-book” questioning means that the AI does not only generate answers from its training dataset in the primordial manner of LLMs, but is also capable of looking up answers on the internet or from various other publicly available sources [25] [26] [27]. How and where this is done can either be left to the model or be directed by a human instructor. If it is the model solely, a beneficial strategy in doing this can be interpreted as another type of intelligent task, broadening

our understanding of today's AI capabilities significantly. The taxonomy presented in this paper can help to evaluate the chances of success of such an undertaking.

### B. Summary

This paper proposes a new classification scheme for evaluating the trustworthiness and usefulness of Large Language Models (LLMs) in supporting everyday tasks, particularly in the context of fact-checking and combating misinformation. We argue that existing benchmarks and metrics are insufficient and often flawed, failing to keep pace with the rapid development of LLMs.

The proposed methodology involves using a questionnaire based on a dataset of questions about widespread everyday wisdom, urban legends, and misconceptions, sourced from the German weekly newspaper DIE ZEIT "Stimmt's" section. The questions are formulated in a "Is it right that..." format, allowing for short answers of "Yes", "No" or "Yes and No." We manually selected 1,000 questions from a total of 1,276, excluding those that were country-specific, potentially offensive, or not suitable for the proposed format. The LLMs' responses to these questions are then compared to the expert-verified answers from the ZEIT dataset, and a point-based weighting scheme is applied to rate the LLMs' performance. The scheme assigns points ranging from -4 to +4 based on the agreement or disagreement between the LLMs' answers and the expert-verified answers, considering factors such as the LLMs' ability to identify unknown or uncertain answers and their tendency to confabulate or reproduce common misconceptions.

We tested several well-known LLMs, including OpenAI's GPT series, Anthropic's Claude 3, and others, comparing their performance using the proposed rating system. The results suggest that some LLMs, such as GPT-4-Turbo, GPT-4o, and Claude-3-Opus, achieve "superhuman" or "expert" level performance in debunking common myths. However, the author notes that a more thorough manual comparison of the LLMs' reasoning with the experts' explanations is necessary to fully validate these findings. The paper also examines the confidence scores provided by the LLMs and concludes that these scores do not necessarily improve the quality of the answers or the overall rating of the LLMs' trustworthiness.

### ACKNOWLEDGEMENTS

We would like to thank the referees for very useful comments on the original submission. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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# Human Perception and Classification of AI-Generated Images: A Pre-Study based on a Sample from the Media Sector in Germany

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**Abstract**—Recent advances in Generative Artificial Intelligence (AI) have significantly expanded and improved image generation and processing possibilities. Applications, such as DALL-E, Midjourney, and Stable Diffusion have simplified Generative AI for non-technicians and made it accessible to a broad audience. The quality of the generated images has steadily increased in recent months, with photo-realistic representations almost indistinguishable from real photos. AI-based image generation and editing methods are also becoming increasingly accessible for professional use, where high-quality image generation and editing were formerly reserved for specially trained personnel. However, the perception of Generative AI's results and potential depends not only on image quality. Human users may have reservations or a biased assessment of the performance of AI for image generation, for example, because they doubt the creativity of AI or fear the substitution of jobs. Against this background, a pre-study with a sample of  $N = 172$  participants from the media sector in Germany is presented. The participants were asked about their attitudes towards image-generating AI and had to assess a test set of images regarding quality and type of generation. The results show that while minor differences in quality are observed, classification precision is almost independent of the quality rating and the participants' attitudes or experiences. The study supports the conclusion that even representatives from the media sector cannot systematically recognize AI-generated images based on image quality at the current performance level of image-generating Generative AI.

**Keywords**—Generative AI; AI-based media disruption; AI-generated images; human perception of AI; identification of AI-generated images.

## I. INTRODUCTION

Recent advances have significantly influenced the development of Generative AI in image generation and processing in machine learning and visual computing. In particular, the introduction of Generative Adversarial Networks (GANs) has played a crucial role in automatic image generation with computers. GANs have revolutionized the field by introducing a framework in which two neural networks, the generator and the discriminator, compete against each other to produce high-quality synthetic images [1]. Corresponding approaches to generating realistic images have proven extremely effective and have pushed the boundaries of what AI can achieve in image generation.

In addition, the emergence of Large Language Models (LLM) has significantly influenced the spread of AI technologies within a non-technical audience [2]. These models,

such as GPT-3, GPT-4 and most recently GPT-4o in the ChatGPT application [3], have demonstrated and popularized the potential of using natural language prompts to a mass audience. In this context, creating, modifying, and editing images based on detailed descriptions in natural language has gained notoriety and spread rapidly [4].

By training with huge amounts of data, these models can now understand and interpret human input to produce corresponding visual results, which also democratizes the creation of images with the help of AI. Whereas in the past, more sophisticated types of digital image editing were reserved for experts trained in the operation of specialized software, impressive results can now be achieved by appropriately describing the results as part of the prompt engineering of an image-generating Generative AI.

Since the launch of ChatGPT in November 2022 [5], significant qualitative improvements have been achieved in generating images with AI. For example, ChatGPT and subsequent solutions have demonstrated remarkable capabilities in creating images that closely resemble authentic photographs, blurring the lines between human and AI-generated content [6]. These advances have meant that distinguishing between the two has become difficult, highlighting the rapid progress of AI technology in mimicking human creativity and perception.

However, there are still limitations in the professional use of AI-generated images. Issues, such as maintaining consistency of style, context, and coherence in the generated images remain an obstacle to the productive and regular integration of AI-generated content in various domains. Ongoing research and development work continuously addresses these challenges to improve the quality and authenticity of AI-generated images. Especially, it is becoming increasingly difficult for humans to distinguish real photographs from AI-generated images, which is reflected in the increased research interest in so-called "deep fakes" [7]–[9]. However, the higher performance and greater difficulty distinguishing AI-generated content applies not only to photo-realistic images but also to creative works, such as illustrations and artworks.

Against this background, the remainder of this paper is structured as follows: After this introduction, Section II presents the research background on the attitude towards AI-generated content, image classification, and quality criteria before formulating the research questions of this study. Building on this, Section III presents this study's survey and test design.

Section IV then presents the results of this pre-study, followed by the conclusion in Section V. Finally, Section VI concludes with limitations and an outlook for further research.

## II. RESEARCH BACKGROUND AND OBJECTIVES

This section provides a brief overview of related research in the perception and evaluation of AI-generated imagery and then narrows down the research questions of this study.

### A. Attitude towards AI-generated Content

An important field of research on innovative Generative AI tools is how AI-generated images are perceived. The perception of AI-generated images and art by humans is a complex and evolving area of research. Research suggests that there is a bias towards such computer-generated art. Studies show that people tend to differentiate between AI and human-made art, often undervaluing the former [10]. This bias may be due to the perceived effort involved in creating art, as AI-generated artworks are sometimes seen as less effortful compared to traditional art forms [11]. However, efforts to anthropomorphize AI systems, e.g., by highlighting the role of human programmers and software as collaborators, may help to counteract this bias and facilitate the consideration of AI-generated outputs as genuine artworks [12].

In addition, the attribution of creativity to AI systems plays an important role in how AI-generated art is perceived. Studies have shown that people's attitudes towards AI-generated aesthetics are influenced by their perception of the AI's capabilities and creativity [13]. This could be because Generative AI represents models trained to uncover and replicate design patterns, and therefore, AI is denied the ability to create something novel. Furthermore, the perceived partnership between humans and AI in the creation process, where humans develop the code for AI algorithms and provide instructions to generate art, can increase the value and appreciation of AI-generated artworks [14].

The evaluation of AI-generated art is not only influenced by the artwork itself but also by the context in which it is presented. Factors, such as the explicit and implicit perception of AI-generated art in different cultural contexts can affect how these artworks are received [15]. Furthermore, understanding AI capabilities in generating images in different domains, such as clinical settings, may influence human perceptions of the quality and reliability of AI-generated content [16].

Another tension in the perception of Generative AI tools is that such innovative solutions can be perceived as support or opportunities to increase productivity, but also as a threat to the company's activities and a risk of job substitution [17]. With regard to the application of (Generative) AI in general, there are already studies that aim to estimate corresponding increases in productivity or implications for the workplace [18]–[20]. In the creative and media sector in particular, however, hardly any studies still examine such attitudes and correlations.

In summary, human perceptions of AI-generated images and artworks are complex and influenced by biases, perceived effort, attributions of creativity, cultural contexts, and understanding of AI's capabilities. As AI plays an increasing role in creative endeavors, further research is needed to investigate how these perceptions evolve and shape the interaction between humans and AI in creative industries like the media sector.

### B. Image Classification

There are several different research approaches to the issue of recognizing AI-generated images. Firstly, there are technical approaches that relate, for example, to the analysis of image artifacts and pixel patterns resulting from the generation process [21]. Other approaches use machine learning methods (e.g., Contrastive Language-Image Pre-training (CLIP) [22], Convolutional Neural Networks, and Transfer Learning [23]) to differentiate between real and AI-generated images. In the context of research into deep fakes, several studies have already investigated how humans can distinguish real authentic images and videos – often related to the representation of people or human faces – from those that appear realistic but are faked AI-generated content using deep learning technology [24]–[27].

This study also aims to investigate human's ability to distinguish between images generated with and without AI. However, the focus here is less on the actual recognition performance or the ability to detect non-authentic image material but more on the relationships between the classification decision, perceived image quality, and the attitude towards Generative AI of employees in the media sector. However, there is still a need for research in the media sector, while more research has already been published for AI-generated artwork. For example, several studies have investigated people's ability to distinguish between human-generated and AI-generated art. Chamberlain et al. [10] found a bias towards computer-generated art and emphasized the difficulties distinguishing between human-generated and AI-generated artworks. Gangadharbatla [11] examined the impact of knowledge of art attribution in evaluation and focused on the accuracy of the distinction. Zhou and Kawabata [28], and Gu and Li [29] also investigated participants' ability to distinguish between human-created and AI-generated artworks, with different results in detail. The studies by Lyu et al. [30], and Natale and Henrickson [12] likewise reported mixed results, i.e., some participants correctly recognized AI-generated artworks, while others had difficulty doing so.

Horton et al. [31] emphasized that comparing human and AI-generated art can improve the perception of human creativity. In addition, Fortuna et al. [32] emphasized that individual evaluation schemes influence the differences in evaluating AI- and human-generated artworks. Another study by Ho [33] discussed social and ethical issues related to AI-generated art, while Rasrichai et al. [34] provided insights into how presumed knowledge of an artist's identity influences the evaluation of artworks. With regard to the use of images in the media sector, it is not so much individual attribution, uniqueness, or artistic impression that is important; rather, images are often used for visualization, explanation, and to create context. Therefore, the results from the art sector are transferable, but only to a limited extent. In conclusion, the issue of distinguishing between AI and human-generated imagery has so far been considered primarily from the perspective of art and artists, but there is still a need for research in the media.

### C. Image Quality Evaluation

There are several approaches to evaluating the quality characteristics of an image based on the analysis of corresponding psychological factors and cognitive evaluation processes of works of art. For example, criteria for evaluating image quality could be derived from studies based on established theories

of aesthetic judgment and the psychological processing of art. The model of Leder et al. [35] outlines stages of perceptual analysis, which includes initial reception and basic features, such as color and composition, to cognitive coping and evaluation, which includes more subjective and complex judgments, such as creativity and narrative understanding. Graf and Landwehr [36] propose a model that distinguishes between the pleasurable and interesting aspects of aesthetic experience. Their work is important for understanding how different aspects of an artwork, including its emotional impact and originality, contribute to the overall aesthetic evaluation.

From a simplified transfer of the findings of this work, relevant criteria for the present study can be derived for the qualitative evaluation of images, such as (1) detail and texture quality, (2) color harmony, (3) composition and structure, (4) creativity and originality, (5) emotional impact, and (6) narrative perception. These criteria have not been taken directly from the aforementioned research but are based on essential findings for the evaluation of works of art and transfer them to the quality assessment of images. For further details, it is referred to the corresponding literature [35][36].

#### D. Research Objectives

Based on the previous explanations and the identified research needs, the following research questions have been formulated for this pre-study:

- To what extent are Generative AI tools already widespread in the media sector sample, and how is the work-related impact of this new technology on the working environment perceived?
- How is the quality of AI-generated images perceived, and to what extent does this quality assessment influence the classification of images as AI-generated?
- To what extent is the precision of the classification of AI-generated images of the participants dependent on their experience with digital image processing, AI tools, and attitudes towards Generative AI?

This pre-study will assess these research questions in a sample of working adults from the media sector. The procedure and results are described in the following sections.

### III. SURVEY AND TEST DESIGN

A questionnaire was developed to answer the research questions defined in the previous section. The questionnaire contains parts on the participants' characteristics, experiences, and attitudes toward image generation by Generative AI, as well as a section in which AI and non-AI-generated (real) images are to be evaluated in terms of their quality and classified concerning the type of image generation. The questionnaire had no time restrictions for answering the questions, and the participants could decide how long they wanted to look at the pictures. The structure of this questionnaire is described in more detail below.

#### A. Survey Contents and Structure

The questionnaire was realized as an online questionnaire using the survey software Unipark [37]. The questionnaire was distributed via a link and answered in the web browser. The survey was divided into four sections:

- *Sample characteristics:* At the beginning of the questionnaire, basic demographic information, such as age, gender, educational qualifications, and employment

status, was collected to analyze the demographic profile of the study participants.

- *Experience with digital image editing and Generative AI:* Then participants were asked about their experience with digital imaging and various AI applications for image generation. This involves determining the extent to which the participants have come into contact with digital image editing privately, during their education, or professionally and which specific AI tools they know and use.
- *Attitude towards the impact of Generative AI:* Next, the participants were asked to express their opinion on the impact of AI. This involves an assessment of potential job losses, productivity increases, threats to copyright, and the general quality of AI-generated images compared to human creation.
- *Evaluation of AI and non-AI generated (real) images:* The main part of the questionnaire focused on the evaluation of six different images generated either by humans or by AI. Participants were asked to evaluate various aspects of image quality, including detail, color harmony, composition, creativity, emotional impact, and narrative elements. They also had to assess whether the images shown were created by AI and how confident they were in their assessment.

The questionnaire concluded with individual overall assessments of the difficulty of the classification task and the importance of quality features.

#### B. Image Evaluation and Classification

For this part of the evaluation of images, a set of images had to be defined first. The Kaggle Data Set "AI-Generated Images vs. Real Images" [38] was used for this purpose. Three AI-generated and three non-AI-generated images were selected from the data set to keep the processing time acceptable for the participants. Because the motif could influence the evaluation, three pairs of images with similar compositions were used in each case. The first image was selected randomly, and then a similar composition with a contrary form of image generation was searched for in the data set. It was ensured that no well-known images by popular artists were used and that the images did not contain any watermarks or signatures of artists. The following images were selected for presentation:

- *Photo-realistic images of animals:* A lion in an unnatural pose (AI-generated, Image 1) and a parrot in close-up (real, Image 2).
- *Photo-realistic portraits:* A side portrait of a woman (real, Image 3) and a frontal portrait of a woman (AI-generated, Image 4).
- *Abstract landscapes:* Naive depiction of a country house (real, Image 5) and a colorful abstract valley with a river (AI-generated, Image 6).

The images in the dataset were crawled from the web and cannot be printed here due to unresolved copyrights. However, the filenames provided in the Appendix can identify them in the dataset.

Each image was presented in a separate section in high resolution in the online questionnaire. The respondents were first asked to evaluate the images in terms of image quality using the following criteria as discussed in Section II-C:

- *Detail and texture quality:* Evaluation of the image's perceived level of detail and texture.

- *Color harmony*: Evaluation of the harmony and appropriateness of the use of color.
- *Composition and structure*: Evaluation of the structural composition of the image.
- *Creativity and originality*: Evaluation of the creativity expressed in the image and its originality.
- *Emotional impact*: Determination of the extent to which the image is emotionally appealing.
- *Narrative perception*: Evaluation of whether the image tells a story or conveys a recognizable message.

Participants were also asked whether they thought it was AI-generated or non-AI-generated for each image. In addition, the certainty of the decision was to be indicated, and the quality criteria were to be ranked in terms of their importance in the classification decision, with at least one important criterion to be selected.

#### IV. FINDINGS OF THE STUDY

##### A. Survey Implementation and Sample Characteristics

The survey was conducted via a panel provider in mid-May 2024. The panel included men and women over 18 years who live in Germany and are particularly media-savvy, i.e., come from media companies and media degree programs or have completed vocational training in the media sector. However, there were no filter questions to exclude participants. This was done against the background that the sample was narrowed down to the media sector, but in principle, everyone could participate in the questionnaire. A total of 189 participants completed the survey. Responses less than a quarter or three times as long as the median survey duration were excluded. As a result, 172 responses were left in the sample and analyzed further. As Table I shows, the study participants are predominantly men (60.5%) with a bachelor's, master's, or diploma degree (55.2%) who work as employees (79.7%). The sample is, therefore, not representative of the population in Germany or a specific, definable target group in the media sector. However, this pre-study focuses on fundamental relationships between attitudes towards generating an image with Generative AI and identifying AI-generated images. The results obtained, therefore, remain meaningful as an initial indication but can only be applied to the sector as a whole to a limited extent.

##### B. Digital Imaging Experience and Use of Generative AI

Almost all of the participants have already gained experience with digital image editing in the private sphere or as a hobby (87.7%), in training and studies (68.0%) or at work or in a company (79.5%). These results initially show that knowledge in the field of digital imaging is not only reserved for specialists and experts in a professional context but is now also widely used in everyday life. Comprehensive experience in digital image editing (rather or very many) was found most often in the private sphere and hobbies (50.9%), while such an extent of experience in training and studies (39.0%), as well as at work (49.1%) was less stated. In terms of duration, most of the participants had a total of 6-10 years of experience with digital image editing (none: 18.6%, 0-2 years: 16.9%, 3-5 years: 19.8%, 6-10 years: 26.7%, 11-20 years: 12.8%, 21 years or more: 5.2%).

Table II shows the popularity and frequency of using AI-based applications for image creation and editing in the sample (a selection of tools known and used in Germany was chosen [39]). The best-known applications (the tool is used or at least

TABLE I. SAMPLE DEMOGRAPHICS

	Count	Percentage
<b>Age (Years)</b>		
< 25	6	3.5%
26-35	62	36.0%
36-50	50	29.1%
> 50	54	31.4%
<b>Gender</b>		
Male	104	60.5%
Female	68	39.5%
<b>Highest Educational Qualification</b>		
Vocational qualification	29	16.9%
Bachelor	45	26.2%
Master, Diploma, etc.	50	29.1%
Other	48	27.9%
<b>Employment</b>		
Employee	137	79.7%
Civil servant	5	2.9%
Self-employed	25	14.5%
Other	2	2.9%
<b>Total</b>	<b>172</b>	<b>100.0%</b>

known) are Adobe Firefly (66.7%), DALL-E (54.1%), Midjourney (53.8%), and Bing Image Creator (53.6%). Therefore, more than half of the respondents already know about image creation and editing methods with Generative AI. However, the proportion of those who have already used such applications is significantly lower. Only with Adobe Firefly, more than half of the participants in the study already gained experience of use (50.3%), while this otherwise fluctuates between 39.9% (Bing Image Creator) and 34.5% (Jasper Art). The proportion of those who use Generative AI applications almost daily is still below ten percent and highest for Adobe Firefly (8.8%) and DALL-E (8.1%). The high prevalence of Adobe applications can be explained by the fact that the people in the sample are media-savvy, and Adobe products are the industry standard in the media sector and creative industries.

TABLE II. POPULARITY AND USAGE FREQUENCY OF SELECTED AI TOOLS

	I do not use	I do know, but haven't used it yet	Very rare, only tried out so far	Irregularly, on occasion	Regularly, several times a week	Regularly, almost every day
DALL-E	45.9%	17.4%	8.1%	11.0%	9.3%	8.1%
Midjourney	46.2%	15.2%	9.9%	9.4%	13.5%	5.8%
Stable Diffusion	48.8%	15.7%	8.1%	11.0%	11.0%	5.2%
Adobe Firefly	33.3%	16.4%	10.5%	15.2%	15.8%	8.8%
Bing Image Creator	46.4%	13.7%	6.5%	14.3%	13.7%	5.4%
Jasper Art	46.8%	53.2%	5.8%	12.3%	10.5%	5.8%

In the next section of the questionnaire, the study participants were asked about their agreement with predetermined statements on the impact of using Generative AI tools for generating images ("To what extent do you agree with the following statements on the generation of images with AI?"). A 5-point Likert scale was used for the feedback ("Fully agree", ..., "Do not agree at all"). Figure 1 shows the results for this question as a percentage of the selected response options. For

all six questions, it can initially be seen that around a third of respondents are still undecided about the impact the use of AI will have in this area.

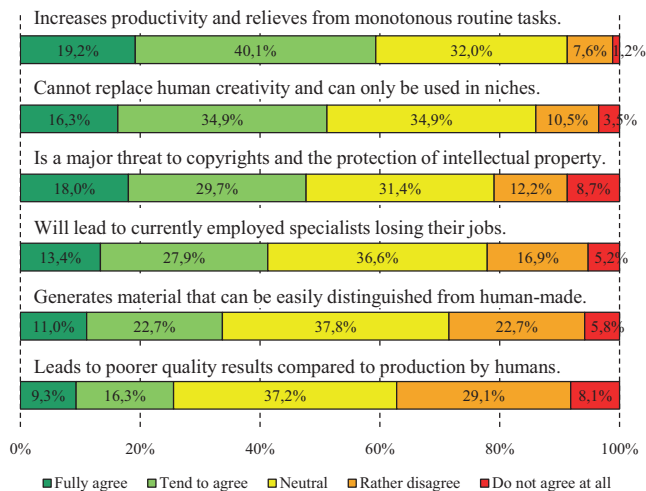


Figure 1. Respondents Agreement Level to Statements on the Impact of AI-based Image Generation.

However, a majority of the participants expect AI to increase productivity and relieve them of routine tasks. Among those who have formed an opinion, the prevailing attitude is that AI cannot replace human creativity and can only be used in niches. The stated agreement also outweighs disagreement regarding the threat to copyrights, the substitution of jobs, and, with a small difference only, that AI-generated images are easy to distinguish. This differs from the statement on the lower quality, which was rejected by a significantly larger proportion of respondents than agreed with. These results thus reflect the findings of other studies that were previously mentioned. Although a certain threat to jobs and copyrights is perceived as a result of image generation with Generative AI, most respondents assume an increase in productivity and expect that the limits of Generative AI lie where particular human creativity is important.

C. Results on the Image Classification Test

Participants were asked to answer questions about six test images in the next section of the questionnaire. In the first step, they were asked to rate the image quality in relation to the previously discussed criteria on a five-point scale (1 = very poor, ..., 5 = very good). Participants could also select “no response”. Table III shows the average ratings across all participants and the overall quality as the average of the six criteria values. The first interesting observation is that the three “real art” images, i.e., those not generated with AI, received the highest overall quality values.

As Table IV shows, most respondents classified only one image as real or not AI-generated. This is a photo-realistic depiction of a parrot, characterized by a high level of detail and color richness. Two images tagged as real art in the image set were incorrectly classified as AI-generated by the respondents. Overall, the classification is largely independent of the image quality, which supports the previous observation in this study

TABLE III. RESPONDENTS’ ASSESSMENT OF THE TEST IMAGES BY THE QUALITY CRITERIA

Image	1	2	3	4	5	6
Generation	AI	Real	Real	AI	Real	AI
Overall quality (average)	3.58	4.28	4.06	3.46	3.70	3.67
Detail and texture quality	3.75	4.47	4.14	3.38	3.66	3.72
Color harmony	3.80	4.47	4.22	3.60	3.77	3.81
Composition and structure	3.57	4.39	4.18	3.49	3.73	3.64
Creativity and originality	3.69	4.11	3.89	3.43	3.74	3.72
Emotional effect	3.33	4.13	3.98	3.45	3.64	3.57
Narrative perception	3.36	4.10	3.95	3.45	3.67	3.59

that the respondents predominantly assume that AI does not generate images of poorer quality. It is also interesting to note in Table IV that most respondents were rather or very confident in their classification decisions, i.e., no major deviations in decision confidence between the images reported.

TABLE IV. RESPONDENTS’ CLASSIFICATION AND CERTAINTY ON AI GENERATION OF TEST IMAGES

Image	1	2	3	4	5	6
Generation	AI	Real	Real	AI	Real	AI
AI	93.6%	31.4%	65.7%	87.2%	69.6%	85.4%
Real	6.4%	68.6%	34.3%	12.8%	30.4%	14.6%
Majority	AI	Real	AI	AI	AI	AI
Very uncertain	1.7%	0.6%	1.2%	1.7%	0.6%	3.5%
Rather uncertain	11.6%	16.9%	19.8%	12.8%	23.3%	15.1%
Rather certain	54.7%	52.3%	52.3%	45.3%	44.2%	43.0%
Very certain	32.0%	30.2%	26.7%	40.1%	32.0%	38.4%

In addition to evaluating the images according to the perceived quality, the participants were asked to rank the quality criteria based on their importance for classifying the respective images as real art or AI-generated. Table V shows the results of this assessment of the importance of the criteria for the various images. From the different levels of importance of the individual criteria in the classification decision on AI generation for the various images, it can be deduced that this ranking strongly depends on the motif. In the first image, composition, structure, creativity, and originality are the most important decision criteria. This fits in with the fact that in this image, a lion is shown in a rather unnatural pose in front of an incongruous background. In the second image, detail, texture quality, and color harmony are the most important criteria, which also fits the motif, as a photographic close-up of a colorful parrot is shown here. The different importance of the criteria and the resulting motif-dependent evaluation profiles are visualized in Figure 2 for Image 1 and 2.

The importance of the criteria thus provides important clues for image-related decision-making. However, the image quality in this respect does not systematically influence the categorization as AI-generated. In Table V for Image 3, for example, the criteria detail and texture quality (3.23) and composition and structure (3.19) are the most important evaluation criteria and were also rated relatively well (4.14, 4.18) in Table III. Nevertheless, Image 3 was classified as AI-generated by the majority of the participants. This can be explained by examining the participants’ free text comments reported in the survey data. The decision to classify the image as AI-



TABLE V. RESPONDENTS' ASSESSMENT OF THE IMPORTANCE OF QUALITY CRITERIA FOR IMAGE CLASSIFICATION

Image	1	2	3	4	5	6
Generation	AI	Real	Real	AI	Real	AI
Detail and texture quality	2.56	3.28	3.23	3.60	2.92	2.84
Color harmony	2.24	3.51	2.68	3.07	3.49	3.41
Composition and structure	3.16	3.01	3.19	3.12	3.07	2.97
Creativity and originality	3.09	2.04	2.28	2.13	2.42	2.62
Emotional effect	2.14	1.83	2.16	1.91	1.98	2.01
Narrative perception	1.80	1.56	1.78	1.42	1.55	1.62

generated was evaluated with statements, such as “exaggerated idealization”, “looks very edited on the face”, “the skin is too perfect”, “the natural is missing”, or “looks artificial”. These ratings are presumably because although this image is a photo-realistic portrait of a woman, it is a real art, not a photograph. Thus, the classification as Generative AI seems less about the perceived quality and more about certain inconsistencies as deviations between expected (photo) and perceived (not a photo) image features, where deviations from the expectations are interpreted as indications of AI generation.

Table V also shows that technical characteristics of the image (detail and texture quality, color harmony, composition, and structure) play a more important role in classification, while perceptions in terms of creativity and originality, emotional effect, and narrative perception are of lesser importance. A reason why primarily technical criteria were used in the image quality evaluation may also be because the participants were unaware of the task and the background of the creation of the pictures. For example, whether an original pose or a realistic depiction was required or the picture idea was not described. Future studies, therefore, should investigate further how the implementation of an image idea is perceived in images created with AI (prompt engineering) and without AI (traditional digital image creation and editing).

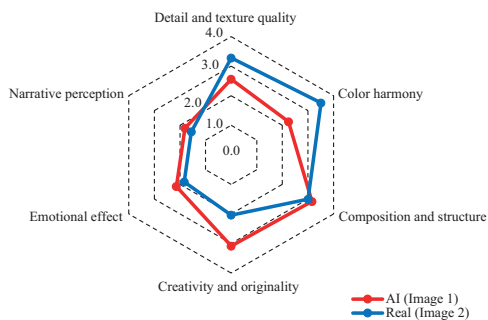


Figure 2. Importance Comparison of Quality Criteria Profile for Image 1 and 2.

#### D. Participant Characteristics and Image Classification

In the final step of the survey data analysis, several correlations were examined between participant characteristics

and the image classification task. As part of this pre-study, simple correlation analyses (due to the partly ordinal scaled variables using Spearman correlation) and significant tests were carried out. Table VI shows the corresponding correlation between selected experience data with digital image editing during education (ExpEdu) and in the work environment (ExpWork), experience with AI tools (AITool), as well as the agreement values for the statements on substitution of jobs by AI (JobLoss), the increase in productivity (ProdImp), the limited potential of AI to replace human creativity (CreatLim), and the ease of differentiation (EasyDiff) of AI and non-AI images which were previously discussed in Section IV-B.

TABLE VI. CORRELATION MATRIX FOR SELECTED EXPERIENCE AND STATEMENTS ON IA IMPACT

	ExpEdu	ExpWork	AITool	JobLoss	ProdImp	CreatLim	EasyDiff
ExpEdu	–						
ExpWork	0.757**	–					
AITool	0.691**	0.642**	–				
JobLoss	0.075	0.026	-0.06	–			
ProdImp	0.230**	0.298**	0.286**	0.028	–		
CreatLim	0.141	0.157*	0.075	0.193*	0.190*	–	
EasyDiff	0.371**	0.396**	0.441**	0.037	0.275**	0.302**	–

Correlation is significant at the \* 0.05/\*\* 0.01 level (2-tailed).

Significant strong correlations can be found between the intensity of the use of AI tools and experience with digital image processing in education and the work environment. The significant weak correlation between expectations of increased productivity and the corresponding experience with digital image editing and AI tools is interesting and plausible. The significant but very weak correlation between the assessment that Generative AI will lead to job losses and the agreement with the statement that AI cannot replace human creativity is unexpected and remarkable. The coincidence of these contradictory statements in the participants' opinions could indicate that the two statements tended to be supported by people with a rather negative or skeptical attitude toward AI technology.

The level of agreement with the limited creativity of Generative AI also correlates very weakly with the extent of the participants' work experience and their agreement with the impact of Generative AI on their working environment. It is interesting to note that the assessment of the ease of distinguishing AI-generated images correlates with almost all other experience and agreement values. The assessment of differentiability is most strongly influenced by the intensity of usage of AI tools. This is plausible, as participants who regularly and frequently use AI tools are expected to be best able to assess the possibilities and results.

The following will examine the influences of the participant characteristics on the test persons' classification results of the pictures. Figure 3 shows the frequency of the number of correct classifications by the participants. On average, 3.99 images were correctly classified by the subjects as AI-generated or not AI-generated. The distribution in the figure indicates that most probably random differences rather than systematic differences are responsible for the differences in the precision of the classification decision.

This assumption is strengthened when the results of the correlation analysis in Table VII are considered. In addition to the variables of the study described above, the experience with

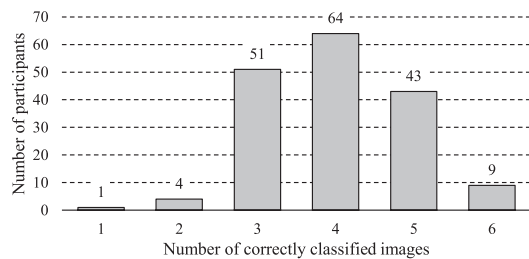


Figure 3. Frequency of Correct Image Classifications.

digital image processing in the private sector (ExpPriv), the total duration of the experience (ExpDur), and the number of correctly classified images (CorrClas) are also listed here. First of all, it can be seen that all experience-related characteristics correlate significantly and considerably with each other. Unexpectedly, however, there is a significant but very weak negative correlation between the number of correctly classified images and experience with digital image processing in training and education, as well as the intensity of the use of AI tools.

This could be explained by the fact that participants with extensive experience also know that very high-quality results can now be achieved with Generative AI and, therefore, considered AI generation to be possible for almost all of the images inspected. The results are nevertheless surprising and indicate that even with extensive experience in digital image processing, it was not possible to classify the test images presented systematically.

TABLE VII. CORRELATION MATRIX FOR EXPERIENCE AND CORRECT IMAGE CLASSIFICATION

	ExpPriv	ExpEdu	ExpWork	ExpDur	AITool	CorrClas
ExpPriv	-					
ExpEdu	0.653**	-				
ExpWork	0.634**	0.757**	-			
ExpDur	0.536**	0.324**	0.460**	-		
AITool	0.589**	0.691**	0.642**	0.285**	-	
CorrClas	-0.138	-0.163*	-0.136	-0.074	-0.180*	-

Correlation is significant at the \* 0.05/\*\* 0.01 level (2-tailed).

In a last consideration, the correlations between the agreement values for the statements of the AI impact and the correct image classification are shown in Table VIII. This table also lists the variables for the agreement values on the statement of a threat to intellectual property (IPThreat) and the poorer quality of AI-generated images (PoorQual). There are also no clearly interpretable relationships here, even though some correlations may indicate a certain basic attitude toward AI. There is a significant, moderate correlation between the perceived risk for Intellectual Property (IP) and the substitution of jobs. The perception of poor quality of AI-generated image material correlates very weakly with job substitution and (weakly) with IP risk and irreplaceable human creativity. However, there is only a significant, very weak positive correlation with the perceived IP risk regarding the number of correctly classified images. This could indicate that those participants who have dealt more extensively with the Generative AI procedures and understand the problem of reuse of design patterns by AI (that

relates to IP problems) were also able to achieve slightly better classification results.

TABLE VIII. CORRELATION MATRIX FOR STATEMENTS ON IA IMPACT AND IMAGE CLASSIFICATION

	JobLoss	ProdImp	IPThreat	CreatLim	PoorQual	EasyDiff	CorrClas
JobLoss	-						
ProdImp	0.028	-					
IPThreat	0.404**	-0.186*	-				
CreatLim	0.193*	0.190*	0.168*	-			
PoorQual	0.178*	-0.100	0.330**	0.356**	-		
EasyDiff	0.037	0.275**	0.086	0.302**	0.325**	-	
CorrClas	0.053	-0.045	0.157*	0.03	0.033	-0.075	-

Correlation is significant at the \* 0.05/\*\* 0.01 level (2-tailed).

As a result, it can be stated that there is no statistical evidence within the scope of the study that certain experience with digital image editing or a high-intensity use of AI tools systematically improves the ability to correctly assign the AI-generated images in the set of images presented. There are also no clear correlations between certain attitudes towards the impact of AI and the classification result. However, it should be noted that this may be due to the composition of the small sample or the selection of motifs, and therefore, the results of this pre-study show a tendency but cannot yet be generalized.

## V. CONCLUSIONS

This preliminary study has provided important findings on the reception of image-generating Generative AI in the German media sector. The following results can be summarized concerning the research questions formulated at the beginning:

- *Use and awareness of Generative AI:* Less than two years after the launch of ChatGPT, about one-half of the participants in this sample from the German media sector are familiar with Generative AI tools for digital image creation and editing. The most common AI tools, such as DALL-E or Adobe Firefly, are already used almost daily by nearly one in ten of those surveyed.
- *Impact of Generative AI:* Around a third of the participants have not yet formed a clear opinion on the effects of Generative AI on their working environment. However, for those with an opinion, the majority agrees with the statements that AI increases productivity and relieves the burden of routine tasks but cannot replace human creativity. The performance of Generative AI is already perceived as very high: The participants are almost undecided as to whether AI-generated images are still distinguishable. Only a minority within the sample perceives AI-generated images as characterized by poorer quality.
- *Quality and recognition of AI-generated images:* While the non-AI-generated images are assigned a slightly higher quality, only one out of three non-AI-generated real artwork images is recognized correctly by the majority of participants. The test shows that quality is not used to draw conclusions about AI generation, and no specific quality criteria are important for the classification decision. Rather, the importance of these criteria varies depending on the motif. Overall, the participants seem to pay more attention to

inconsistencies in the composition of images when identifying AI-generated images.

- *Factors influencing image classification:* The correct recognition of images in the image set presented cannot be explained systematically by the experience or attitudes of the participants, although there was a tendency to overestimate the proportion of AI-generated images. However, it is interesting to note that the correlations examined reveal some relationships between more skeptical or positive attitudes toward the impact of AI.

Based on these results, it should be noted that there is still a great openness towards using Generative AI. However, there are already skeptical perspectives on its use, which could increase if negative expectations prove true. For example, fears regarding the risks of copyrighting an IP threat must be effectively countered. It is difficult and will certainly become even more difficult to distinguish AI-based images from the creative work of humans by the end product. Thus, it can be expected that the human element in creative collaboration with AI and the added value of a human expert must be explained and emphasized more to customers in future media productions.

## VI. LIMITATIONS AND OUTLOOK

The results of this pre-study are based on a sample obtained via a panel. The users received an incentive for their participation. Although participants from the media sector were specifically contacted for participation, there were no filter questions or quotas to obtain a representative sample for the media sector in Germany. Against this background, the results can only be generalized to a limited extent. The test is also subject to several limitations. With only six images presented, the participants were exposed to a very small test set. The choice of motifs may also have influenced the results, as the selection was not purely random but rather pairs of similar compositions of AI-generated and non-AI-generated images.

However, based on this study's results, whether larger and more representative samples or more comprehensive and randomly selected image tests could generate more meaningful findings is questionable. The study results indicate that with the current state of image generation with Generative AI, even experts are often unable to make a reliable decision about the type of image generation based on the images produced or their quality. Rather, subsequent studies should focus on the image generation process. Therefore, future studies should consider the underlying goals or idea of image generation and let participants evaluate the resulting images in relation to the image idea. In addition to a binary setup (with and without AI), it could be interesting to investigate how collaboration between humans and AI affects the production process and the results. The design of such human-AI collaboration processes in the media and creative sector appears to be an important field of research that has remained largely unexplored.

## APPENDIX

The following information specifies the images from the Kaggle dataset "AI-Generated Images vs Real Images" [38] used in this study:

- Image 1: AI-generated, filename: 41b6d9592db18a15b1e32dfd50.jpg.
- Image 2: Real, filename: shouts-animals-watch-baby-hemingway.jpg.
- Image 3: Real, filename: portrait075a-819x1024.jpg.
- Image 4: AI-generated, filename: 52520977911\_33437880be\_z.jpg.
- Image 5: Real, filename: tature-scenery-poster-500x500.jpg.
- Image 6: AI-generated, filename: clgjljiec001a08k0bhi51i88.jpg.

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# Human or AI?

## Exploring the Impact of AI Tools on Audio Content Production and Perception

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**Abstract**— There is a growing trend of people consuming audio content in Germany. As a result, many media companies have invested in audio content in recent years. With the help of Artificial Intelligence (AI) tools like Elevenlabs or MurfAI, producing high-quality sound has become relatively easy. The first part of the study aims to determine if media users can differentiate between AI-generated and human voices and how they perceive AI-generated audio content compared to human-generated content. In the second step, the analysis wants to determine how AI influences the content's credibility and the users' willingness to pay for audio content.

**Keywords-AI; Audio content; Podcasts; Credibility; Willingness to pay**

### I. INTRODUCTION

Germany has a growing trend of using audio and video content for information and entertainment. In Germany, nearly 53 million individuals aged 14 and above used at least one audio service every working day in 2023. On average, users listen to audio services for more than four hours a day [1]. The younger demographic has shown a particular interest in podcasts, enabling media to reach well-educated, affluent target groups who are moving away from traditional news consumption [2]. Some experts observe a shift from written to spoken content, as people value the ability to listen while engaging in other activities.

Publishing houses are increasingly investing in audio content, taking advantage of the growing popularity of audio formats. Many media companies in Germany are now offering podcasts and audio versions of their written articles [3]-[6], and the trend of audio content will continue. Advancements in AI technology are also driving the surge in audio content. AI tools, such as text-to-speech technology, have made it possible to create more natural-sounding speech, improve audio quality, and enhance personalized recommendations [7]. This has allowed media companies to work more efficiently, reducing production costs and time. AI tools like Elevenlabs or MurfAI have made adding high-quality audio to content easier, enabling the replication of emotions, tones, accents, and even translation into different languages [8]. Many media companies and podcasters now rely on various AI tools for content conceptualization, production, post-production, and marketing. Despite these advancements, more research is needed on how audiences

perceive AI-generated voices. The study aims to address the research gap by answering the following research questions:

1. Can participants distinguish whether a voice is human or synthesized by an AI tool?

2. Does the use of AI tools impact the credibility of content or the willingness to pay for it?

Section 2 of the paper focuses on related audio production and AI literature. Section 3 explains the methodology. Section 4 considers the first results of the study. Section 5 provides a conclusion, and the last section addresses the limitations of the study.

### II. RELATED LITERATURE

Many newsrooms have used artificial intelligence for various purposes, such as personalized content, fact-checking, and content production [9]-[13]. AI tools have helped media companies save costs and time. Before the introduction of ChatGPT, some media companies used algorithms to report on stock market developments and weather forecasts. In recent years, the focus of using algorithms in legacy media has been on automated texts and research comparing texts written with the help of algorithms with those written by humans [14].

A recent comprehensive analysis by Thurman et al. examined how media users in the UK perceive human-made, partially automated, and highly automated short-form videos. The researchers found that the participants did not detect huge differences between the differently produced videos [15]. A representative study conducted in the USA, Germany, and China, covering audio, image, and text, shows that test subjects need help distinguishing human-generated content from AI content [16].

With the constant improvement in the quality of text-to-speech tools, an increasing number of media companies, such as *Neue Züricher Zeitung*, *Süddeutsche Zeitung*, and even regional newspapers like *Rheinische Post* are offering the option of reading articles aloud [17]-[19]. Additionally, the emergence of AI tools for creating and optimizing audio content, such as Elevenlabs or MurfAI, has led to many media houses using these tools for audio content production. These tools can be used to optimize audio recordings and even to clone voices.

In this study, we will focus on human, cloned, and artificial voices used in podcasts and for the read-aloud

function on media company websites. The study aims to discover how AI affects audio content perception and whether people can detect humans from cloned or artificial voices.

Studies by industry services, such as Bitkom, show that it is essential to media users that journalistic content notes whether AI has been used [20]. However, the effects on willingness to pay and credibility in the audio sector still need to be determined. The study also wants to fill this research gap.

### III. METHODOLOGY

In the first step, we conduct a within-subjects experiment. We ask participants to listen to different audio files and determine whether the voice was produced by an AI tool or a person. After each test, we conduct individual-focused interviews based on the experiment results. This method allows for detailed and profound questioning [21]. According to Mayring, content analysis is used to categorize and analyze the interviews [22]. In the last step, we will inquire in a brief survey about the participants' socio-demographic aspects, audio use, and willingness to pay for audio content, such as podcasts. The study also aims to understand the importance of test subjects knowing whether AI was used in creating journalistic content and how this information affects the perceived credibility of the content and the willingness to pay for it.

#### A. Stimulus materials

The study required test subjects to listen to audio content (human, cloned and artificial voices). The experimental stimuli were divided into podcasts and audio voices, which offered the service of reading articles published on media websites. Ten different audio files from various areas, such as politics, business, sports, and regional affairs, were selected for the study. The order of the examples presented to the participants was altered to prevent potential learning effects. The following files were played for the test subjects:

##### 1) Podcasts:

- The Episode about Russia and Ukraine - the cloned voice of the host
- The Episode about Russia and Ukraine - the human voice
- The Episode about the search for a new trainer of FC Bayern - the cloned voice of the host
- The Episode about the training of FC Bayern - the human voice
- The Episode about new AI tools - the cloned voice of the host

##### 2) Spoken Articles:

- Salaries at RWE - the cloned voice of a reporter
- Queer people in Hamburg - artificial voice
- Here I come - an article about reckless people - the cloned voice of a reporter.

Additionally, the participants were asked to compare the human voice and the cloned voice generated by the AI tool Elevenlabs from two different podcasters.

#### B. Participants

When selecting test subjects, we ensured a balanced ratio of men and women. The test subjects were required to have experience listening to a podcast or using the option of having a text read aloud on a website. Nine test subjects took part in the first test run, which was conducted via Zoom in May 2024 (see Table 1).

TABLE I. LIST OF PARTICIPANTS

Number	Participants			
	Sex	Age	Podcast use	Audio use
1	Female	45-54 years	yes	yes
2	Male	55-64 years	no	stopped using it
3	Female	55-64 years	yes	stopped using it
4	Male	55-64 years	no	stopped using it
5	Female	35-44 years	yes	stopped using it
6	Female	25-34 years	yes	stopped using it
7	Male	45-54 years	no	stopped using it
8	Male	55-64 years	yes	stopped using it
9	Male	35-44 years	yes	stopped using it

Some of the test subjects listened to podcasts regularly. All of them had tried having an article read to them at least once. However, the respondents had one thing in common: everyone except one respondent no longer used this service. The unanimous argument was that the audio output quality needed to improve, and listening to the artificial voice was challenging. Some also mentioned that they preferred scanning a text for interesting passages rather than listening to an audio recording. One test subject utilized the read-aloud feature to have articles in foreign languages read out loud. Nevertheless, all test persons were surprised at how the quality of AI-generated voices improved.

### IV. FIRST RESULTS

The initial results have shown that none of the test subjects could identify all AI-generated voices. This result is consistent with those of the study by Frank et al. Media users need to be informed about the use of AI tools in producing media content. The test subjects even felt that the information that AI was used needed to be increased. They would like to know precisely for which production steps the editors or podcasters have used AI. For example, the test subjects find listening to an AI-generated voice less problematic - if they like the voice and intonation. However, the situation is different when AI is used to research content. Respondents are particularly skeptical about journalists using AI for research. For instance, respondent 3 mentioned, "I experiment extensively with AI tools and therefore know

that the answers are not always perfect. That is why I would not trust AI-generated content in journalism." However, as our first results show, providing information about the use of AI tools can lead to lower credibility. Nevertheless, respondents are divided when it comes to their willingness to pay. Many would not be willing to pay the same price for journalistic content if it were generated with the help of AI tools.

## V. CONCLUSION

In the first step of our research project, we wanted to find out if people can detect humans from cloned and AI-generated voices. This is relevant because many media offer audio content using AI tools. Our first results show that the probands could not say if a voice were human or artificial. Even though people could not detect differences in the audio examples provided in the test, people said that media should indicate if and for what steps in the value chain media used AI tools. However, the information on the use of AI tools generally affects the content's credibility and willingness to pay for it.

## VI. LIMITATIONS

It is important to note that our study is ongoing. With nine test subjects, the sample is still tiny. We will expand our study by analyzing audio and video content and testing it with more test persons. We will ask probands to listen to audio and video content produced with the help of AI tools and produced by humans. We will use the usability lab of HNU conducting an eye-tracking test, and a facial expression analysis using the software iMotions. We will meticulously analyze the emotions evoked during audio and video consumption. Even if initial results show that hardly anyone succeeds in distinguishing AI-generated voices from human voices, people may react differently emotionally to the content or fixate on other content with their eyes in AI-generated videos.

While we have initial results, a comprehensive analysis and further testing are still underway. We look forward to sharing these additional insights shortly.

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## Exploring the use of Gen-AI by International Students in France

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**Abstract**—Today, many students smartly use generative artificial intelligence to help write their dissertations, either Master or doctoral. Concerning students who do not have a good command in English nor in French, it is often difficult to write prompts and to understand answers. So, they have to juggle between several languages. In this paper, we will examine their strategies to reach the desired results, overall from languages for which corpora are reduced and avoiding sophisticated words. Their strategies can be characterized as iterative and multilingual with a multi-bot approach. We will conclude by giving with some recommendations when using Gen-AI and some suggestions for chatbots developers.

**Keywords**—component; Generative AI; Gen-AI; Chatbots; International Students; Dissertations; Cultural differences.

### I. INTRODUCTION

CPU-Lyon (Coup de Pouce Université) is a non-for-profit organization whose goal is to help foreign university students in their studies. Located in Lyon, France, CPU has around 300+ international students coming from 68 countries accompanied by 142 volunteers teaching them French as a foreign language (levels A1, A2, B1, B2, C1, C2) [1], accompanying them in writing their Master or doctoral dissertations and receiving them in families.

In this paper, we will only focus on international students who have to write a dissertation.

The role of volunteers is not to replace that of dissertation supervisors but, beyond the correction of French is to ensure that the characteristics of this particular literary genre are well respected. They must thus verify the correct writing of research questions and assumptions, the coherence of the state of the art, the adequacy of the chosen methodologies, the good presentation of references, etc. Typically, the student meets the accompanying volunteer 2 hours per week.

Facing this aspect, essentially because of the paramount importance of cultural differences, a research program was launched at CPU-Lyon to analyze how international students use generative AI (Gen-AI) chatbots not only to write their dissertations, but also to write preliminary reports. For that purpose, it was decided to organize interviews and the objective of this paper is to present the results.

So, the aim of this paper is to describe the strategies used by international students to achieve their objectives, and also to offer some suggestions for them and for chatbot developers. But before, it looks necessary to remind some characteristics of international students. Table I shows the origin of international students at CPU.

TABLE I. ORIGIN OF INTERNATIONAL STUDENTS AT CPU AS OF JUNE 2023. COUNTRIES WITH LESS THAN 1% ARE NOT LISTED.

Continents	%	Some origins of students
Europe (14 countries)	16%	Albania (4%), Spain (2%), Ukraine (1%)
Far East (12 countries)	37%	China (19%), Taiwan (3%), South Korea (2%), Japan (3%), Vietnam (5%), India (4%)
Middle East (11 countries)	16%	Afghanistan (6%), Iraq (1%), Iran (4%), Syria (4%), Saudi Arabia 2%, Lebanon 2%
Africa (19 countries)	14%	Algeria (2%), Soudan (2%), Egypt (2%)
America (11 countries)	14%	Brazil (2%), Colombia (4%), Mexico (2%), Peru (1%)

*Mutatis mutandis*, we think that the results of this study can be interesting for foreign students in other countries such as USA, UK, Germany, etc.

### II. GEN-AI AND ACADEMIA

Now, since the advent of generative AI, the problem of helping students is now changing [2]. Of course, the total generation of a dissertation is not tolerated in many doctoral schools' codes of conduct, but the "intelligent use" of AI is accepted [3].

Since the problem is recent, apparently few studies have done concerning university students. For instance, a study made in Hong-Kong [4] shows that the results show that students recognized the potential for personalized learning support, writing and brainstorming assistance, and research and analysis capabilities. However, concerns about accuracy, privacy, ethical issues, and the impact on personal development, career prospects, and societal values were also expressed. More generally, the Russell Group [5] has pointed out five principles: (i) Universities will support students and staff to become AI-literate; (ii) Staff should be equipped to support students to use generative AI tools effectively and appropriately in their learning experience; (iii) Universities will adapt teaching and assessment to incorporate the ethical use of generative AI and support equal access; (iv) Universities will ensure academic rigor and integrity is upheld; (v) Universities will work collaboratively to share best practice as the technology and its application in education evolves. See also [6].

According to [7], while artificial intelligence is of high interest in higher education, ethical and critical reflection on the issues it raises in this particular context is less advanced,

so that “technical application” and “ethical and critical reflection” are not well secured at present in academia.

Moreover, a university [8] gives a list of dos and don’ts when using Gen-AI tools. For dos, it mentions use GenAI for brainstorming, check for factual accuracy of AI-generated content, use AI-generated content in conjunction with other sources to ensure that the work is reliable and well-informed, and include any GenAI assistance in the reference list; and for don’ts, do not rely solely on AI-generated content as the source of information, do not ask GenAI software to write your essays, do not input any personal details or confidential information when using GenAI tools.

However, sometimes chatbots deliver misinformation, fake news and hallucinations which are inserted into answer or portions of answer out of concerns.

Several studies concerning teaching a foreign language, especially English in China [9]: the results support the notion that AI-mediated language instruction holds promise in revolutionizing language learning, and it highlights the positive impact of AI-driven educational technologies in the realm of language education. Whereas [10] shows that quantitative analysis reveals significant improvements in both writing skills and motivation among students who received AI-assisted instruction compared to the control group.

Moreover, several universities host international students who have specificities. Table II gives the number of international students: those numbers come from Google Gemini and are of 2023.

TABLE II. TABLE SHOWING THE TOP 10 COUNTRIES WITH THE MOST INTERNATIONAL STUDENTS, BASED ON 2023 DATA. SOURCE: GOOGLE GEMINI

Country	Number of International Students	Country	Number of International Students
USA	914,000	UK	605,000
Canada	551,000	Australia	489,000
China	492,000	Germany	355,000
France	348,000	Japan	312,000
Russia	300,000	India	246,000

Regarding international students, a study [11] in South-Korea is targeted to the use of Gen-AI for helping them together with academics in their daily lives in the campus, but not targeted to the assistance in their studies.

In addition, another paper [12] dedicated to international students illustrates problems and challenges considering only some minor cultural differences done in a very superficial manner. However, the authors insist on the fact that using a chatbot allows international students to maximize their learning potential and stay on track with their studies, even with limited access to their professor due to language or cultural barriers.

### III. SOME SPECIFICITIES OF INTERNATIONAL STUDENTS

International students are characterized by three types of barriers, linguistic, cultural and linked to technology access including Internet. Let us begin by technology access.

#### A. About barriers concerning technology access

Some international students originate from countries with high technological environment where computerized work is already commonplace (therefore with a potential openness to AI). Conversely, others have very limited use of computers, because of problems of network connection and energy availability (Africa, part of Middle East).

The diffusion of Internet is variable according to languages. Table III gives the percentages of website in the world ranked by languages, but slightly differently percentages are given in [13], nevertheless the ranking is similar. With this table, one can easily see that English language is predominant whereas Chinese and Arabic languages, even if the number of locutors is very high, the relative percentage of websites is very low. In other words, the distribution of website does not correspond to the distribution of spoken languages.

TABLE III. PERCENTAGE OF WEBSITE RANKED BY LANGUAGES. THE SUM IS GREATER THAN 100 BECAUSE SEVERAL SITES HAVE VERSIONS IN DIFFERENT LANGUAGES. SOURCE: MICROSOFT COPILOT.

Language Name	Number of Speakers	Website Percentage
English	1,500,000,000	55.5%
Mandarin Chinese	1,100,000,000	2.8%
Spanish	460,000,000	4.9%
French	280,000,000	4.1%
Arabic	310,000,000	3.3%
Russian	258,000,000	0.8%
Portuguese	220,000,000	2.6%
German	90,000,000	2.0%

Concerning international students who do not have good commands neither in English nor in French, they can face difficulties not only to get information in their own native language, but also to run systems based on Gen-AI. For instance, this is the case for Albanese, Estonian and Finnish students for which usual automatic translators are not provided.

#### B. Linguistic Barriers

Among the linguistic barriers, let us mention the levels of French and English languages but also the fact that in their native language some concepts do not exist. Indeed, they often speak without fully grasping the nuances between different language registers: formal, informal, addressing superiors, slang, and even scientific, or professional registers. We can also add the more recent one, which pertains to conversing with a conversational AI such as a chatbot. Not to mention occasional mixtures of French with English.

Moreover, it has been observed that, for them often unlike young children, reading is easier than speaking.

Indeed, when faced with reading difficulties, a doctoral student can consult a dictionary, whereas rarely in oral communication they dare to ask for explanations about specific words. While listening, especially in lectures, they might confuse one word with another, or get lost because of the so-called “false friends” between the language of the lecturer and their own language.

In addition, one of the specific rules in French rhetoric dictates to avoid repetition, which necessitates finding equivalent expressions or even using circumlocutions. In contrast, in other languages like English, this rule is absent. Let's take the example of King Charles III of England. One might have a sentence beginning with the British sovereign, another with "His Majesty", and later mention Elizabeth II's son, Camilla Parker Bowles's husband, the head of the Commonwealth, the former Prince of Wales and so on. Ignoring these variations, one might mistakenly believe they are dealing with multiple individuals when, in fact, it is the same person.

Let us apply a similar reasoning for scientific or philosophical concepts, as a consequence a doctoral or Master student is totally lost when reading a text in French language or listening a lecture.

Another aspect is that in France, some so-called English words or expressions have no meaning at all in English so to perplex students (for instance “parking” for car park, “smoking” for dinner suit or tuxedo, “chips” for crisps, “break” for estate car or station wagon, “footing” for to jog or to run, etc.).

### C. Cultural Barriers

For instance, when trying to quickly comprehend a Buddhist text, you do not understand anything if you have not been introduced to these notions very far from our Greco-Latin and Judeo-Christian civilization!

By definition, culture encompasses the customs, beliefs, language, art, and practices shared by a group of people. It defines their collective identity and shapes their way of life, i.e. the relationships with humans, with nature and with knowledge. So, international students are shaped according to their home culture whereas they have to acclimate to the culture of the country in which they study (here France). In addition, some of them must face a third culture for writing their dissertation (for instance English).

Indeed, for all foreign doctoral students, the situation is common where they encounter difficulties in understanding new concepts and notions.

Another barrier comes from the various educational backgrounds those students have received with different program and methodologies even in disciplines such as engineering and medicine.

Styles of learning are different among the societies, and it may have a strong impact on the way students use AI.

1 – For example, there are countries where learning is strongly teacher-centered, with few interactions and weak possibilities of exchange (Middle East, China, Japan). It can be assumed that the dialogue function of the chatbot may not be easily used. In other words, students originating from this culture will accept chatbot's answer without challenging the

validity of the answer and then will have difficulties to structure a dialog.

2 – In other cases, learning is mainly obtained by problem-solving and case discussions (North America, part of Europe) for which AI could be a positive tool if students are trained to use it that way.

Styles of learning are also different according to individuals, as the extensive use of Kolb's Learning Styles Inventory [14] proves it. People preferring conceptual abstraction, or reflexive observation, for instance, could have distinct AI strategies (further research is needed on that topic).

### D. Other barriers

There are other barriers which have a great importance for international students, but with minor impact on Gen-AI. Let us rapidly detail few of them.

Both in English and French, sometimes some Latin expressions are used; even for Spanish-speaking students, due to the different pronunciation, they have difficulties to understand.

From Greek and Latin mythologies, from Bible and Christianity, some allusions are not well understood by most Asiatic students.

In some Gen-AI answers, some stereotypes have been discovered. For instance, all French people are supposed to wear berets, lazy and prone to strikes.

The so-called “politically correct” generates circumlocutions which are not immediately understood by international students.

Among additional difficulties, one must consider some expressions from literature and history. For instance, Waterloo is seen as a disaster for Frenchmen whereas a victory for Englishmen. See also issues linked to colonization viewed differently from colonizers and local people.

## IV. METHODOLOGY

To explore the various strategies carried out by CPU international students, we decided to make interviews. A preliminary informal guide was designed with some questions relative to their discovery of those tools, their usage for different purposes, their difficulties and their opinion concerning ethical issues.

Please mention that all the following interviews have been made in French, and then the results were translated into English for this paper.

### V. SOME INTERVIEWS AND STRATEGIES

Based on the previous guide, twelve students were interviewed. The answers span from two extremities:

1 – Strict ethical position; *by principle, I don't want to use Gen-AI because this is cheating and plagiarism, and the produced text is not mine.*

2 –Towards AI-augmented humans: *I can no longer live without chatbots because they are a valuable help to me.*

However, many students have visions less radical than the previous ones. Let us detail a few of them. For privacy

reasons, the first names have been changed. See Figure 1 for the geographic distribution of interviewed students.

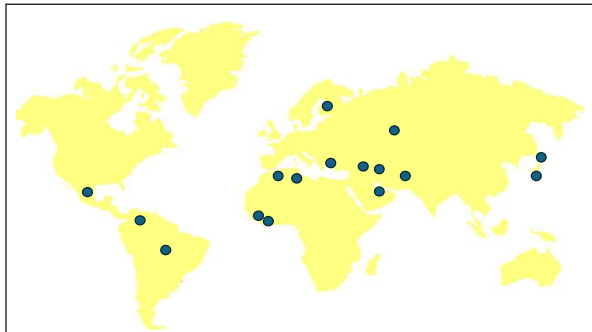


Figure 1. Origin of interviewed students.

#### A. Francisca's case

Francisca is a Venezuelan student in economics and has to write her master's dissertation in English, but the *viva voce* exam will be in French: she juggles between Spanish, English and French. For this purpose, she uses several tools. Listen to her!

##### 1) Text understanding

"The first aspect is the comprehension of texts (C1 level), especially in English, texts that I must study for writing. If I stumble on a word, I use Linguee or Reverso; if I stumble on a sentence or a paragraph, I use rather translators like Bing translator, Google translate. Depending on the case, the target languages are French or Spanish."

##### 2) Understanding of sophisticated concepts and words

"I use Gen-AI products to understand certain concepts by being aware that often the French and Spanish concepts are neighboring while those in English are a little different. Depending on the case, I start from the concept in English or Spanish and try to draw satisfactory explanations, and therefore I start a chat with ChatGPT or Copilot. If necessary, I change language. Whenever the answer uses sophisticated words, I ask to have them replaced by more common words. Sometimes when I am hesitating about French verbs, I run conjugation software."

##### 3) Help for writing in English

"Sometimes I write directly in English. If I am not satisfied, I ask either for polishing my text or for a complete reformulation until the result suits relevant. When I am less sure of the quality of my own English, I write a paragraph in Spanish, then it is translated into English: I check every time whether the translation is correct, without wrong interpretation. In doubt, I launch a re-translation into Spanish as insurance. In other words, I run a sort of multilingual discussion."

##### 4) Oral assistance in French

"In order to prepare my *viva voce* defense in French, I use the possibilities of generating abstracts and hears the results be prepared especially when I am hesitating about the pronunciation of a word in both for French and English,

In addition, I use the functionality to generate slides."

#### B. Sepideh's case

She is an Afghan student in finance. She wrote her Master dissertation in English.

##### 1) Corpus of languages

"I speak several vernacular languages of Central Asia, but these languages are unknown to translators and generative AI systems because they are characterized by too few speakers listed on the Internet, in short, too small language corpora to base deep learning. I also juggle between languages to arrive to texts corresponding exactly to what I want. Moreover, I have sometimes difficulties because my native language does not have certain concepts."

##### 2) Confidentiality

"Coming from a country where the place of women is absent, I am mainly concerned by confidentiality. Indeed, as these AI systems use other conversations for their learning, I fear for my freedom of expression. Thus, to improve the presentation of my CV in English, I decided not to use deep learning systems."

#### C. Dimitri's case

Dimitri is a Russian student of fine arts. "I have a poor command of French (B2) and very poor English (B1). I am wary of Gen-AI systems because they sometimes deliver totally or partially false information. When I stumble on a word or phrase, I look for synonyms or quotes using them. In addition, I use chatbots to polish my French and English, and to understand grammar.

For my bibliographic search, once I received two references, say Author#1, Title#1, and Author#2, Title#2. After checking, I discovered that the reality was Author#1, Title#2, and Author#2, Title#1: the titles had been reversed! So, having found that references were fanciful or absent, I prefer the classic way of search engines (Google, Qwant, Duckduckgo, etc.) by adding keywords.

Due to my low level in French, I am afraid of writing my dissertation."

#### D. Lee's case

Lee is PhD student from South Korea, often using the assistance of Gemini, as suggested by a Korean professor.

"I mainly use Gen-AI to correct mails. The French people I know do not have time to brush my texts. Gemini proposes corrections and explains its propositions, it is very useful (generally better than ChatGPT)."

##### 1) Reformulation of sentences

"I do not want always to ask Gemini to correct or reformulate a complete text, because it will not be my own text. But sometimes I integrate a paragraph judged relevant. Anyway, my supervisor will read my text and correct it from the point of view of the ideas."

##### 2) Bibliography

"For example, when I am requested to read a book about an author, I search immediately his/her bibliography, or I ask Gemini about the meaning of some concepts. I do think this is very useful, but a check is necessary because of many errors."

### 3) *Quantitative analysis*

“When I have to make a quantitative analysis by means of another software product, and I desire a comment, or if there is an error, I ask Gemini by pasting the error message and it answers.”

### 4) *Legal information*

“Since my doctoral subject concerns legal information, I consider Gemini very useful.

Finally, I have decided not to write completely my dissertation with Gemini, for the reason that I want to write my own personal text. Anyway, I consider that if I am not the author of the text, and my professors will discover it! Indeed, I believe that it looks very easy to detect whether a text is written by Gen-AI. Is it a fraud? I guess it is possible to discover if the text has been made with the assistance of Gen-AI and for the researcher, there is a question of honor!

There was no training about AI in my origin university, no payment of subscription for AI, everybody deals with that individually.

In conclusion, I am optimistic about AI because it will provide a lot of services, and the market competition will maintain low prices.”

### E. *Wei's case*

Wei is a Taiwanese student at Master level, studying French literature. “I frequently use Chat; it answers to question and writes texts. Once I gave a report to my supervisor, but she said that there were paragraphs off topic. So, she discovered that I used a chatbot! Sometimes, Chat gives ideas not in accordance with the subject. Now, I always tell whenever I am using Chat.

Now my professor has integrated Chat in her course. Sometimes, she gave us the text already written by Chat and ask us to improve it. Very difficult! Because the students must examine the logics, the argumentation, the articulations, the examples...

I guess that the professors are going to give the students exercises that Chat is unable to make! For example, to combines four different texts!

My professors demand the students to tell when using Chat.

In literature, it is more difficult to cheat with AI (question of style, sensitivity...)”

### F. *Ali's case*

Ali is a PhD student in sociology from Guinea-Conakry. “I don't use Chat and the others. My wife neither. My supervisor agrees with me to do a doctorate without any artificial tool. I don't need any translation or adaptation since I am francophone.

The thing I fear the most is to produce a text which will not be really mine. I understand that these tools can save some time. I am sure that they will be used in Africa. But I fear that AI will replace a real reflection. Research is a craft and must remain it.

Of course, I am not opposed to use some modern tools (database resources, perhaps computerized data analysis). I will need written transcription of my interviews, but I will discuss this aspect with my supervisor.

Surely it will induce strong change in learning methods.

I am not afraid of frauds and cheat. The professors will easily detect a text which has been written by AI. And the universities are implementing ways of regulating the use of AI.

For Africa, the use of AI will raise a lot of problems: cost, energy, network availability...”

### G. *Luisa's case*

Luisa is doctorate student, from Brazil.

“I discovered Chat thanks to a (French) friend. I was always asking him to revise my French texts, and he said that Chat will do that very well. I have been amazed: corrections, revisions, reformulation...it works well.

So, my main use is for daily mails. I use Chat as a secretary (I don't use Gemini or the others). It proposes answers to my mails, I can ask it to change its tone etc. I can't live without it by now...it is my companion. The only restriction is the possible contrast between my way of French speaking and my text (if I meet the person to whom I have written). I use chatbot intensively, it answers as if it understood, I reply etc.

I use it also for answering questions.

For my thesis, I will use it but anyway I will make the text read by a francophone. Finally, he will understand the content and propose better formulations than Chat. In the research world, everybody uses it, but nobody speaks about it.

I am using it, but I am not optimist for the future. For images, there will be a lot of possible cheats. For writing, I fear that new generations will lose the competency to really write a text, with an introduction, a reasoning, etc. a loss of linguistic competencies, because it is said that writing is inspiration but also transpiration. They will lose the transpiration aspect. I fear that the young will lose the core of intellectual work.”

### H. *Ahmed's case*

Ahmed is from Kuwait, preparing a doctorate in Laws, but with a very low level in French). “I use only translators. Having a good command of English, I write my dissertation in Arabic and English, and translate it immediately in French by using Google, Reverso, or DeepL. And then I compare the results. My CPU volunteer helps me to improve the French text if necessary, and above all to read it. and understand it. I also have difficulties for reading in French, and to pronounce it. I have not tried to use the vocal functions. My CPU volunteer tells me that I should be able to orally understand the questions, and to answer to them. I have not used any AI system to get documentation and resources.”

### I. *Other cases*

On February 27, a group of students was collectively interviewed, and they explain similar experiences. In this paragraph, to avoid repetitions, only complementary information will be mentioned.

They all had experiences with chatbots except Bulent (Turkey, Geography) and Nihel (Tunisian, Anthropology).

Mohammed (Iraq, Political Sciences) used ChatGPT to generate draft slides for one of his slideshows. Valeria (Mexico, Pharmacy) used bots for retrieving various types of pharmaceutical information. Mokhtar (Algeria, Ancient Literature), after difficulties for translating literary Arabic into French, decided not to trust Gen-AI bots anymore. Myriam (Syria, Medicine) told that she uses bots for explanations regarding French grammars and conjugation and tenses of irregular verbs.

Concerning Adama (Guinea, Laws), her mother tongue is Fulani which is not processed by Gen-AI bots, even if it is spoken by between 25 to 40 million people in West Africa [15]. So, she must use another language.

To those students, we also asked whether they used vocal functionalities for prompts: all were not aware about vocal prompts and they decided to use these functionalities.

#### J. Provisional synthetic remarks

For the moment being, only twelve students have been interviewed and our objective is to increase this number and build a questionnaire to be submitted to all CPU students so to get statistics. Anyhow, a few patterns have already been identified:

- obvious help for improving texts in French, overall for documenting, correcting and reformulating;
- use of different chatbots, sometimes intensively and frequently;
- no real different technical problems of writing prompts;
- none has attended a formal training on using Gen-AI tools;
- often, students passively accept answers of translations without any problem and neglect to check the meaning of words and their pronunciation; this attitude can have a negative influence on their command of the target language;
- when the mother language is not processed by bots, an intermediary language will be used to get results in the target language;
- since their aim is to write a dissertation, they look more interested to improve their writing skill, instead of speaking and understanding skills;
- chatbots do not give enough explanations concerning the choice of vocabulary and references;
- very different points of view about ethical problems ranging from optimistic to pessimistic;
- several rely more on their supervisors, not on chatbots;
- none seems interested in paying for using chatbots.

Anyhow, some patterns have been already discovered about the strategies used by the interviewed students. In summary, their strategies can be characterized as iterative and multilingual, together with a multi-bot approach allowing the students to deal with various points of view as schematized in Figure 2. Indeed:

- **Multilingual**, because they need to transform their initial idea of text in their own native language into the target language, via translations, reformulations,

clarifications of concepts, etc. If there is no translator from their native language, they use another language with which they can conceptualize their idea of text.

- **Multi-bot**, because according to the specificity of the task at hand and their knowledge about existing Gen-AI bots, they select the most suitable; sometimes they perform the same things with different bots aiming to converge towards the best possible answers.
- **Iterative**, because the re-do the previous tasks several times until a satisfactory text emerges.

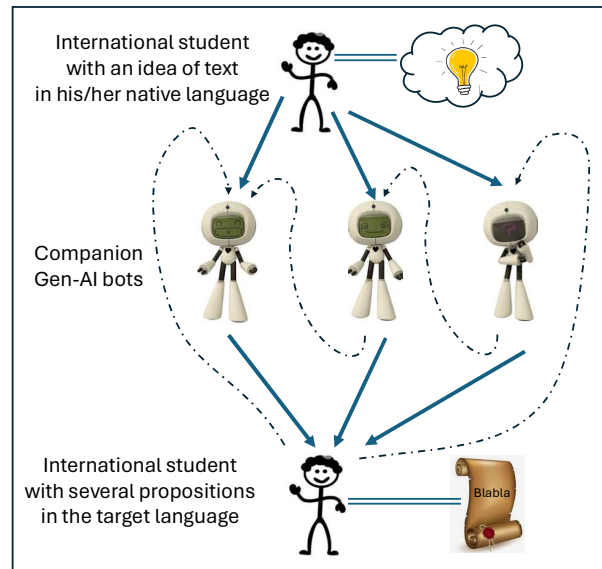


Figure 2. Schematization of the strategies for Gen-AI-assisted dissertation writing used by international students.

Furthermore, some recommendations can be listed together with suggestions to Gen-AI bot developers.

#### VI. RECOMMENDATIONS FOR INTERNATIONAL STUDENTS

Based on the previous interviews, other discussions with CPU volunteers and our own experiences, here is a set of some best practices which can be of interest for writing a Master or a doctoral dissertation. However, a preliminary golden rule could be as soon as a Gen-AI system delivers a text, ask yourself whether you would have written it yourself. If the answer is no, look for hallucinations or ask to reformulate this text until you can endorse a responsibility of authorship.

It must be considered as a preliminary list of best practices which can be extended lately. The first ones are targeted to all kind of students and the subsequent ones specifically for international students.

- **BP1**: remember that the scope of a research dissertation is to produce and validate novel knowledge, whereas a GenAI product will generative a text based on already published knowledge.

- BP2: do not use a GenAI product to generate a whole dissertation; in general, the obtained text is trivial [16].
- BP3: as soon as a text is AI generated, check and double-check it to remove hallucinations and fake information.
- BP4: regarding bibliography, GenAI can be of assistance for the beginning, but after never use a GenAI software to create a relevant bibliography; use instead search engines with Boolean conditions.
- BP5: when you get an interesting paper, generate a summary by GenAI software and translate it into your native language to test whether it really concerns your research questions.
- BP6: if you suspect misinformation, hallucinations or fake news, you are demanded to check and double check.
- BP7: when asking for scientific references to a GenAI bot, verify their quality and prioritize those that undergo rigorous quality control.
- BP8: feel free to employ multiple chatbots to gain diverse perspectives.
- BP9: do not look for innovative suggestions from chatbots, because they are based on existing corpora.
- BP10: please mention explicitly that you are using a chatbot in your dissertation.

Let us pass to best practices specifically dedicated to international students.

- BP11: if you have not good command either in English or in French, write initially your text with your native language, and then launch a translation. Again, check and double-check especially if there are words or expressions you do not understand.
- BP12: if you are at B2/C1 level, write a first version directly in French, and ask for reformulation; you will increase your vocabulary.
- BP13: do not hesitate to ask the same question in different chatbots, in different languages and at different dates; each answer will provide additional insights.
- BP14: if you are hesitant about a verb tense, use a conjugation software.
- BP15: if the answer is full of sophisticated words, launch a reformulation for replacing them.
- BP16: if the answer contains unknown words, check their meaning and the pronunciation.
- BP17: while the short-term objective is to write a successful dissertation, do not forget that the long-term objective is to be fluent in the target language.

#### VII. RECOMMENDATIONS FOR CHATBOT DEVELOPERS

After having listed a few best practices for international students to use intelligently chatbots through various strategies, we think that this is also the role of GenAI developers to take the specificities of international students into account. Indeed, even if English is commonplace, other requirements must be integrated. To the potential clients, one can easily add international researchers working in many

laboratories all over the world. In addition to academia, many businessmen can be interested by those functionalities in their multilingual negotiations.

However, every week a new Gen-AI bot is proposed and marketed: maybe a fresh one could already integrate some functionalities targeted to international students.

As far as we know, Gen-AI systems are developed with the assumption that the user is good in languages such as English or French. Our study leads us to identify 6 profiles of our international students (types 5 and 6 concern students whose native language is not processed but chatbots):

- Profile 1: good in French, good in English
- Profile 2: good in French, bad in English
- Profile 3: bad in French, good in English
- Profile 4: bad in French, bad in English
- Profile 5: good in native language, good in French
- Profile 6: good in native language, bad in French.

Of course, we assume that all international students are fluent in their own respective mother language or dialect. But, due the existing limited lexical fields in those languages, sometimes students have difficulties regarding the mastering of some scientific concepts. In addition, we observe that prevailing chatbots are designed for the three first profiles, but not for the three last ones.

Following our study, here are a few suggestions of requirements for future systems.

SG1: propose to provide answers with simple words and simple grammar.

SG2: if the prompt is not grammatically correct, propose to polish it and to explain simply why this is not correct.

SG3: provide translation to/from all official languages (f.i. Albanese, Fulani, etc.).

SG4: provide a functionality to check a text and a translation (perhaps coming from another Gen-AI bot) to explain the choices made by the translators.

SG5: in discussions, consider chats using different languages in different queries on the same topic (multilingual discussion).

SG6: unveil the key-aspects and requirements towards multi-bot interoperability.

#### VIII. CONCLUSIONS

The scope of this paper was to study the specificities of international students and present the challenges they can face when dealing with Gen-AI bots: they range from linguistic and cultural barriers to technological ones. After having interviewed a few students, some strategies have been unveiled: by varying language proficiency levels, students encounter challenges related to vocabulary and paragraph writing. To achieve their desired results, they navigate between different chatbots, addressing both comprehension and composition aspects. Their strategies combine iterative strategies, multilingualism together with a multi-bot approach.

Then, following those interviews, some best practices have been discovered, first for international students and then for Gen-AI bot developers, a few requirements are suggested.

The initial objective of this paper was to explore the ways CPU international students use Gen-AI especially for writing their dissertations by interviewing some of them. Now, some patterns have been identified, and a more rigorous questionnaire must be built to get statistics.

To conclude this study, apparently Gen-AI bots have been designed with the background that everybody has a good proficiency in English or in his/her native language: this assumption is too strong when observing not only the difficulties international students are facing in their daily use of Gen-AI bots but also the various strategies they use to reach the desired results.

#### ABOUT AUTHORS

RL and YL are volunteers at CPU-Lyon in which they are in charge of helping international students to write their dissertation. RL is professor emeritus in information technologies and YL in sociology. Together they author two books of recommendations for writing doctoral and Master dissertations, one in French [17] and the other in English [18].

#### ACKNOWLEDGMENT

We thank all students and volunteers at CPU [19] for having helped us for this research. And also, we are very grateful for the companies providing free chatbots. We mention that there is no external funding for this work.

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# Using Bi-Directional Instance-Based Compatibility Prediction for Outfit Recommendation

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**Abstract**—Existing fashion recommendation studies focus primarily on recommending individual items. However, this paradigm cannot cater to user needs on fashionable outfit. To obtain a fashionable and well-coordinated outfit, outfit recommendation focuses not only on one item but on all items in an outfit. Such fashion recommendation outputs multiple images of items to constitute a whole outfit. To this end, this paper proposes a novel outfit recommendation method named Bi-directional Instance-based Compatibility Prediction (BICP) suggesting suitable revised outfits based on the outfit inputs of users. In this method, the conditional Bi-directional Long Short-Term Memory (Bi-LSTM) mechanism is used as a backbone to generate the embedding representation of fashion items. To approximate the best outfit, a new metric called I2I-cos (Instance-to-Instance) cosine similarity is also proposed for outfit compatibility calculation. Finally, we made distribution diagrams indicating the outfits recommended by the proposed approaches better align with people's aesthetics and preferences.

**Keywords**- outfit recommendation; fashion compatibility; Bi-LSTM; deep learning.

## I. INTRODUCTION

Fashion is a form of self-expression and autonomy that dictates what we wear, including clothing, footwear, bags, and accessories. With the rise of fashion e-commerce, people can sell and buy apparel online. Therefore, online retailers have invested significant resources to implement machine learning techniques for fashion recommendation. Existing studies for fashion recommendation can be broadly split into two groups: complementary item recommendation [9][10][11] and outfit recommendation [1]. Generally, complementary item recommendation is proposed to suggest a single item for some things that have been matched. Outfit recommendation actually recommends a full set of coordinated items to form an outfit. The most recent studies primarily focus on complementary item recommendation, overlooking outfit recommendation.

However, outfit recommendation must take into account the compatibility of items to suggest suitable outfits. Therefore, modeling the compatibility of items is the key to

outfit recommendation. Figure 1 illustrates the examples of compatible and incompatible outfits. In this paper, we propose a novel recommendation mechanism for outfit recommendation to suggest suitable revised outfits corresponding to the given category based on the outfit inputs of users. In addition, we also propose a new metric for outfit compatibility prediction in these recommended outfits. Finally, we conducted an objective evaluation of the recommended outfits through distribution diagrams to understand whether the outfits recommended by our methods align with human aesthetics.



Fig. 1. Examples of (a): compatible outfits and (b): incompatible outfits.

The remainder of this paper is structured in the following. The related research is briefly reviewed in Section 2. In Section 3, the proposed method for outfit recommendation and the metric for outfit compatibility prediction are presented in detail. The experimental analysis is interpreted in Section 4. Finally, the conclusions and future works are shown in Section 5.

## II. RELATED WORK

As shown in Figure 2, research on Fashion Compatibility Modeling (FCM) can be roughly categorized into pairwise-based [6], sequence-based [5], and graph-based [3] methods. Pairwise-based methods focus primarily on the compatibility between two given items. For example, Song et al. [12] proposed a multi-modal pairwise compatibility modeling scheme with a dual auto-encoder network to match the top and bottom of the outfit. Sequence-based methods think of an outfit as a sequence or a set and each item in the outfit as

a time step and model the task as a sequence problem to uncover complex compatibility relationships among items. Han et al. [8] proposed sequentially modeling the compatibility of items in a given outfit with a Bi-LSTM model to carry out a fashion compatibility prediction task, mainly performing two tasks: complementary item recommendation and compatibility prediction. This study regarded an outfit as a specific ordered sequence of fashion items' images. For a sequence of images, the goal is to recommend suitable items in any position of sequence. Bi-LSTM [4] is proposed for Natural Language Processing, containing forward and backward LSTMs. In the forward direction, Bi-LSTM predicts the feature distribution of the next item based on the previous image features, and Bi-LSTM predicts the feature distribution of the previous item based on the image features in the backward direction. Graph-based methods have recently attracted attention as they excel at enhanced item relations. Such methods model the outfit as a graph in which nodes represent outfit items and node edges represent relations between items. Given this graph, graph neural networks are used to calculate outfit compatibility. Cucurull et al. [2] utilized a graph neural network to learn item embeddings conditioned on their context and cast the FCM task as an edge prediction problem. Iyer et al. [7] embedded a bi-level graph attention mechanism into a graph neural network, increasing the prediction quality. Wang et al. [14] aimed at the heterogeneous graph neural network using the hierarchical attention mechanism.

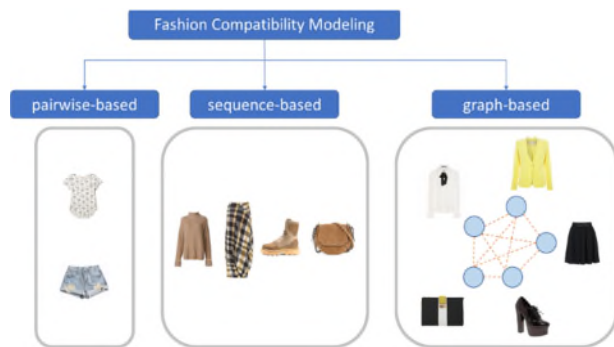


Fig. 2. Three kinds of fashion recommendation.

### III. PROPOSED METHOD

In this section, we will present the details of proposed method, including preliminary definition, framework and compatibility calculation.

#### A. Preliminary

In the proposed method, we employ the pre-trained Bi-LSTM model as the expert-like embedded model which is extended from Han et al.'s approach. We also employ Han et al.'s compatibility prediction concept [8] to propose two novel compatibility methods to evaluate outfit compatibility, which focus on the compatibility effect of each outfit. The major uniqueness of this paper include: 1) the first and the last fashion items are fixed, and 2) our approaches use faster

compatibility calculation methods than Han et al.'s. Here, we define an outfit  $O$  as a sequence  $(I_1, I_2, \dots, I_N)$ , where  $I_j$  is the  $j$ -th fashion item, and  $N$  is the number of items in the outfit. We adopt the pre-processing method for a set of items' images proposed by Han et al. using the pre-trained Inception-V3 model [13] on ImageNet to extract their feature vectors. Thus, we re-define an outfit  $X = (X_1, X_2, \dots, X_N)$  where  $X_j$  is the feature-vector representation of the  $j$ -th fashion item in the outfit. Note that  $O$  and  $X$  have variable lengths because different outfits may have different numbers of items.

#### B. Overview

The method framework is shown in Figure 3. It performs compatibility prediction based on the Bi-LSTM framework during inference time. An outfit formed by the item images is treated as a sequence, and the images are extracted by the pre-trained Inception-V3 model on ImageNet separately and then input into the pre-trained Bi-LSTM model to sequentially predict the next item conditioned on previously seen items — both forward and backward — calculating the similarity of the features to accomplish outfit compatibility prediction. Next, the BICP approach is executed. In BICP, we fix an outfit's head and tail items in the prediction process, meaning the first and last items of the new outfit are the same as those in the original input outfit. The middle part of a new outfit is formed by combining the predictions from the two expert models. Then, the Instance-to-Instance (I2I) similarity indicating the cosine similarity between two instances is calculated. Finally, the suitable outfit and its compatibility score are returned.



Fig. 3. Framework of the proposed method.

#### C. Bi-directional Instance-based Compatibility Prediction (BICP)

We use the Bi-LSTM characteristics to form new outfits. Since Bi-LSTM predicts feature vectors in the next positions in a bidirectional manner, the head and tail items are two main constraints to initialize the process. Therefore, in the proposed approach, we fix an outfit's head and tail items in the prediction process, meaning the first and last items of the new outfit are the same as those in the original input outfit. The middle part of a new outfit is formed by combining the predictions from the two expert models, similar to Han et al.'s complementary item recommendation approach [8]. Yet, we directly calculate feature similarity scores using cosine similarity to expedite the recommendation process. In addition, we restrict the recommended items to be of the same category as the items in the input outfit.

Therefore, the middle part of the new outfit is formed in the following way. For generating the item at the  $t$ -th position in an output outfit, our method uses the Bi-LSTM model to predict the FW feature vector and the BW feature vector of the item. In the forward direction, given the first  $t-1$  items,  $X_1$  to  $X_{t-1}$ , FW predicts the feature vector  $H_{t-1}$  of the

item  $X_t$  at the  $t$ -th position. In the backward direction, given the items of  $X_N$  to  $X_{t+1}$ , BW predicts the feature vector  $\tilde{H}_{t+1}$ . Formally, the item's feature vector in the  $t$ -th position (except the head and the tail) of the output outfit is built as follows:

$$X'_t = \arg \max_{Y_k \in C_t} (FWScore(H_{t-1}, Y_k) + BWScore(\tilde{H}_{t+1}, Y_k)), (1)$$

where  $t$  is the position that we seek to adopt as a sequential instance, which is between 2 to  $N-1$ .  $C_t$  dataset (choice set) is formed by the same category as the item  $X_t$  at the  $t$ -th position, and each item  $Y_k$  is processed to extract feature vectors using the pre-trained Inception-V3. We use the cosine measure ( $\cos$ ) to calculate the similarity between  $H_{t-1}$  and  $Y_k$  to calculate the FW feature score (denoted by  $FWScore$ ). We also do the same for  $\tilde{H}_{t+1}$  to get a BW feature score (denoted by  $BWScore$ ). Hence, FW and BW expert models independently calculate the similarity of one candidate belonging to the outfit, and the candidate with the highest total score is selected at the  $t$ -th position. Now,  $X'_t$  represents the new item's feature vector. We obtain the feature vector of the item and retrieve the original image of this item  $I'_t$ . We thus form the middle part of a new image-form outfit.

#### D. Compatibility Calculation: Instance-to-Instance $\cos$ (I2I-cos)

After performing BICP, we obtain a new image-form outfit. Ideally, the newly generated outfits by the model are the same as the input outfit, indicating that the model considers this outfit to be the most suitable combination. We also employ the concept of Han et al.'s compatibility prediction to assess the overall outfit compatibility by computing feature similarities.

#### Algorithm 1:

The Procedure of BICP Evaluated using the I2I-cos Method

**Input:** A sequence of outfit items  $O$  and its outfit length  $N$

**Output:** A suitable outfit and its compatibility score

1. new\_outfit  $O' = []$ ;
2.  $X = \text{Inception-V3}(O)$ ;
3.  $(H, \tilde{H}) = \text{Bi-LSTM}(X)$ ;
4. **for**  $j = 1$  to  $N$  **do** // BICP
5.   **if**  $j == 1$  or  $j == N$  **then**
6.      $O'[j] = O[j]$ ;
7.   **else**
8.      $X'[j] = \text{recommend}(H[j-1], \tilde{H}[j+1])$ ;
9.      $O'[j] = D'(X'[j])$ ;
10.   **end if**
11. **end for**
12. **for**  $t = 1$  to  $N$  **do** // I2I-cos
13.    $CS = \cos(X'[t], X[t])$ ;
14.    $\text{I2I-cos-CS} = \text{I2I-cos-CS} + CS$ ;
15. **end for**
16.  $\text{I2I-cos-CS} = \text{Avg}(\text{I2I-cos-CS})$ ;
17. **output**( $O'$ ,  $\text{I2I-cos-CS}$ );

Fig. 4. Algorithm of BICP with I2I-cos.

Therefore, we propose the method to directly calculate the cosine similarity between two instances that the pre-trained Inception-V3 transforms the feature representations.

At each position in the original input outfit, the compatibility score is computed for the generated new outfit. The cosine similarity serves as the compatibility score for each instance. Since an outfit consists of multiple instances, we sum the compatibility scores calculated for each position and take the average to obtain the overall compatibility score for this input entire outfit:

$$E(\theta_f, \theta_b) = \frac{1}{N} \sum_{t=1}^N \cos(X'_t, X_t). (2)$$

where  $X'_t$  represents the newly generated instance at the  $t$ -th position, transforming into a feature vector using the pre-trained Inception-V3 model on ImageNet, and  $\cos$  represents the cosine similarity. The above method is the compatibility metric approach. It is called I2I-cos, which is in the range of  $[-1, 1]$ . In an ideal scenario, the calculated compatibility score is 1 which also shows whether the iteration will converge. To better illustrate the iterative process, we use the following Algorithm 1 (Figure 4) to show the complete pseudocode for an understandable representation. Besides, Figure 5 is an illustrative example referring to the proposed algorithm.

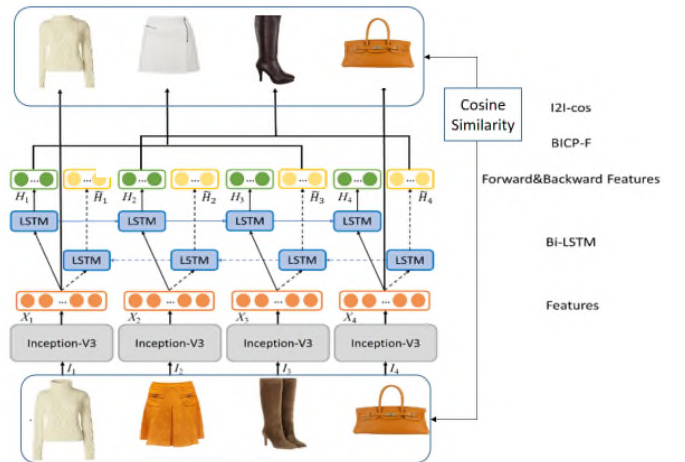


Fig. 5. Architecture of BICP with I2I-cos.

## IV. EXPERIMENTS

After describing the proposed method, this section will show the evaluation for the proposed method.

### A. Experimental Data

The outfit dataset collected by Han et al. from the Polyvore website contains 21,889 outfits and 164,379 items. It is split into 17,316 outfits for training, 1,497 outfits for validation and 3,076 outfits for testing. Each outfit length is between 4 to 8. Each item has the corresponding image, text description, and category (such as jeans and skirts, with 380 kinds of categories in total). To evaluate the performance of our proposed methods, we utilized the fashion compatibility prediction data created by [8], which contains 7076 outfits, of which 3076 are compatible and 4000 are incompatible. Compatible outfits are those that have already been well-matched in the testing set, and their compatibility scores are labeled as ones under the Han et al.'s standard. Incompatible

outfits are created by randomly selecting fashion items from the testing set, and their compatibility scores are labeled as zero.

### B. Experimental Settings

To test our proposed method, we directly used the trained model from Han et al.'s approach. We likewise initialized the Inception-V3 parameters to those pre-trained on ImageNet. We extracted a 2048-dimensional (2048D) feature vector for each image using a pre-trained Inception-V3 model and transformed it into a 512D vector as the input to Bi-LSTM using a fully connected layer. The number of hidden layer units in the forward and backward LSTMs was set to 512. We set the number of iterations to 4. The fashion recommendation programs in this paper were implemented in Python, running on a server with NVIDIA Tesla V100 16GB, Intel(R) Xeon(R) Gold 6140 CPU 2.30GHz and 128GB RAM.

### C. Experimental Results

Figure 6 shows the distribution diagrams of I2I-cos scores for the original compatible input outfits and the recommended outfits derived by the proposed approach. Comparing the two diagrams, we may find the recommended outfits has higher scores than their input even the original input has been with a high compatibility. This means that the proposed approach can improve the outfit quality in average by the proposed recommendation method BICF.

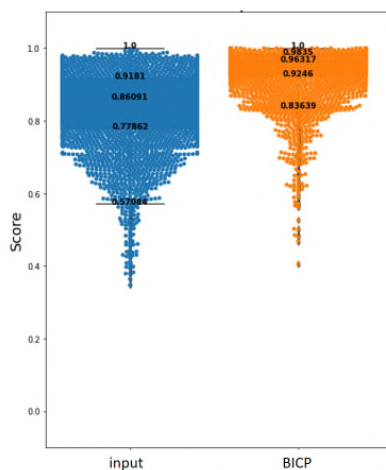


Fig. 6. BICP on compatible outfits evaluated using I2I-cos.

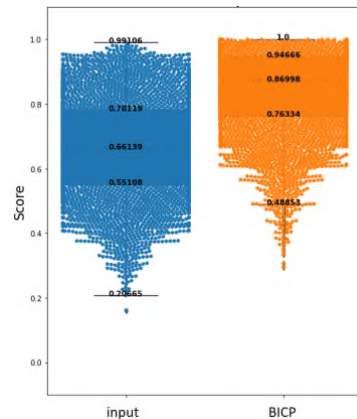


Fig. 7. BICP on incompatible outfits evaluated using I2I-cos.

Figure 7 shows the distribution diagrams of I2I-cos scores for the original incompatible input outfits and the recommended outfits derived by the proposed approach. Since the original input outfits are incompatible, their scores spread wider and are lower in average. In this case, the proposed approach can recommend good outfits and has a significant improvement of the scores. Therefore, the overall score distribution tends to move upwards and become more concentrated.

## V. CONCLUSION

In this paper, we have proposed a novel outfit recommendation mechanism to suggest suitable revisions corresponding to the given category based on outfit inputs of users. The mechanism allows users to input an outfit consisting of a set of their preferred images of items, given which the system will suggest a more suitable one with higher compatibility than the original. We extend Han et al.'s approach by predicting one item, using faster similarity evaluation, and specifying that they are of the same category as the items in the input outfit to form the whole outfit for suggested clothing items. We also employ Han et al.'s compatibility prediction concept to propose a novel evaluation method to evaluate outfit compatibility for the proposed mechanism. Finally, the outfits with higher compatibility scores are recommended. Through the distribution diagrams, it is evident that the proposed outfit recommendation method indeed recommends highly compatible outfits to users. In the future, we will extend this work without fixing the head and tail to reveal the flexibility.

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# Comparison of Large Language Models for Deployment Requirements

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**Abstract**—Large Language Models (LLMs), such as Generative Pre-trained Transformers (GPTs) are revolutionizing the generation of human-like text, producing contextually relevant and syntactically correct content. Despite challenges like biases and hallucinations, these Artificial Intelligence (AI) models excel in tasks, such as content creation, translation, and code generation. Fine-tuning and novel architectures, such as Mixture of Experts (MoE), address these issues. Over the past two years, numerous open-source foundational and fine-tuned models have been introduced, complicating the selection of the optimal LLM for researchers and companies regarding licensing and hardware requirements. To navigate the rapidly evolving LLM landscape and facilitate LLM selection, we present a comparative list of foundational and domain-specific models, focusing on features, such as release year, licensing, and hardware requirements. This list is published on GitLab and will be continuously updated.

**Keywords**—generative AI; large language models; model comparison, HuggingFace.

## I. INTRODUCTION

Large Language Models (LLMs) like Generative Pre-trained Transformer (GPT) are advanced Artificial Intelligence (AI) models designed to generate human-like text in response to the input they receive. These foundational models differ in underlying architecture, training procedures, and training data. They are trained on vast datasets containing a diverse range of internet text. They work by predicting the next word in a sequence, making them proficient at generating coherent sentences, and even writing poems or computer scripts.

The ability of LLMs to generate contextually relevant and syntactically correct text has revolutionized fields, such as content creation, customer service, and software development. LLMs are also integral in developing tools for language translation, summarization, and question-answering systems, enhancing accessibility and efficiency. Furthermore, they contribute significantly to research in natural language understanding and generation, pushing the boundaries of AI's capabilities in understanding complex language constructs.

However, LLMs can produce hallucinations, i.e., generating biased or incorrect information, which raises major concerns about their use in sensitive areas like law and healthcare. To address these drawbacks, pre-trained models are fine-tuned with domain-specific, task-specific corpora or instructions. Another method is Mixture-of-Experts (MoE) LLMs, where a set of LLMs (experts) attend to different parts of the input space. This concept is similar to ensemble methods in traditional machine learning, where the outputs from a set of models are voted to provide a single, more accurate outcome.

Despite these challenges, LLMs continue to be a pivotal area of research and development, resulting in a vast number of

scientific articles. New jargon has rapidly emerged concerning the operation and evaluation of LLMs, including terms, such as prompt engineering, instruction-based fine-tuning [1], and Retrieval Augmented Generation (RAG) [2]. Additionally, the evaluation of the accuracy and performance of LLMs has been questioned, leading to the proposal of various metrics [3]. Multiple surveys have been published that provide comprehensive insights into recent advancements [4][5], discuss evaluation metrics from the perspective of explainability [6], and aim to align LLMs with human expectations [7].

In addition to closed-source cloud-based LLMs like ChatGPT, numerous models have been uploaded to HuggingFace for community use. However, these models vary in features, such as model size, embedding dimensions, and max token count, with details listed on platforms like HuggingFace and Github, and surveys [4][5]. This variability makes it challenging for companies and researchers to select an LLM that meets specific requirements, particularly when the model is intended for local deployment.

The aim of this study is to provide a comparative list of foundational and domain-specific models to support companies and researchers in selecting LLMs. In section II, we explain some of the existing LLMs lists, their content, and the parameters with which they are compared. In section III, we detail which models are selected and which features are compared. In section IV, basic statistics about the listed LLMs are provided, and a part of the comparison list is shown. In section V, further information is given about how the list will be maintained in the future and the limitations of this study.

## II. RELATED WORK

As of May 2024 when this study was performed, HuggingFace had approximately 65 pre-trained LLMs for text generation tasks pertaining to the English language. Additionally, many fine-tuned models, based on the pre-trained models, have been uploaded to HuggingFace [8]. This platform has a couple of leaderboards that compare the fine-tuned models using a framework for few-shot language model evaluation [9]. The Open LLM Leaderboard compares models regarding their type, architecture, model precision, average accuracy, as well as accuracy values calculated separately using various datasets and benchmarks. Another leaderboard is Massive Text Embedding Benchmark (MTEB) Leaderboard illustrating the model size, memory usage, embedding dimensions, max tokens, average overall accuracy from 56 datasets, and average accuracies for classification, clustering, pair classification, reranking, retrieval, STS, and summarization from 12, 11, 3, 4,

15, 10, and 1 datasets, respectively [10]. A total of 281 models are compared with 159 datasets for 113 languages. LMSYS Chatbot Arena Leaderboard is a crowdsourced open platform to evaluate LLMs [11]. As of April 24, 2024, 91 models were evaluated using 800,000 human pairwise comparisons to rank them with the Bradley-Terry model [12]. Additionally, there are some Github repositories [13] and websites [14] that provide rough comparisons. Note that none of these leaderboards provides comprehensive details when companies and researchers encounter technical challenges when they deploy an LLM on their own hardware.

These tables compare the success scores of the LLMs along with their basic information (e.g., type and architecture) but omit the requirements for deployment. Including these requirements is essential to streamline the feasibility analysis process when selecting the most suitable LLM. Our comparison list addresses these needs by providing information on hardware and licensing requirements.

### III. PROPOSED WORK

In this study, we created an extensive comparison list of LLMs for researchers and companies to simplify LLM selection. Since there are numerous fine-tuned models, we primarily focused on covering base foundational LLMs, as much as possible. Nevertheless, some existing domain-specific (e.g., in the medical domain) fine-tuned models were included. We then defined the model features that help users to select the correct LLM. To easily distinguish between different LLMs, we provided both LLM names and families together with the model features, such as release year, license types, and hardware requirements.

The outcome of this study, in the form of a comparison table, is published on a GitLab page for community use. Since new LLMs and their derivatives are continually being developed, this is an ongoing effort, and the GitLab page will be updated regularly[15].

#### A. Model Selection

We selected 108 LLMs based on the criteria of being open-source and having been published in or after 2023. Approximately 20 of them are foundational LLMs, such as Mistral, LLaMA-2, LLaMA-3, Code LLaMA, Gemma, RecurrentGemma, Falcon, Dolly, etc. Some fine-tuned LLMs, such as BioMistral, Meditron, and Medicine-LLM, as well as several MoE LLMs (e.g., Mixtral, Grok-1, and DBRX) were included.

#### B. Model Features

We included information on LLM families and the versions existing within the LLM families. The sizes (i.e., number of parameters) and release dates were listed to track the gradual development in this field.

Furthermore, we also investigated the commercial aspects of the listed open-source LLMs and listed the license information. Since understanding the licenses can be difficult for readers,

in another column, we clarified if the licenses allow for commercial usage of the model (with or without any restrictions) or not.

In addition, we included information on minimum memory requirements (RAM and vRAM) and required disk space for complete fine-tuning and inference. Note that these requirements are applicable for loading the 5-bit quantized versions of the models. Loading models with full-precision floating point numbers usually requires twice or four times more memory relative to their parameters.

### IV. RESULTS

A small subset of our resulting table is shown in Table I [15]. The information on LLMs, along with their families, license, and memory requirements is listed to provide a quick overview of the LLMs for the specific needs and use cases of researchers and companies.

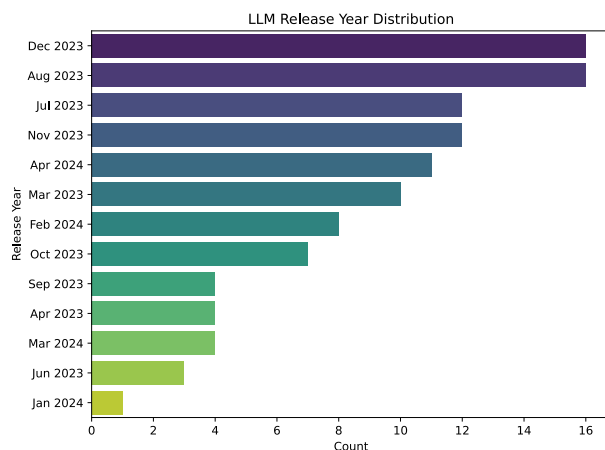


Figure 1. Release Year Distribution of Listed LLMs

Figure 1 shows the distribution of release date, indicating that; most of the LLMs we listed were released in 2023. Note that the most recent LLMs on our list were released in April 2024.

Figure 2 shows the distribution of model size, indicating that; most of our listed LLMs have 7 billion parameters. The size of the rest of the models ranges from 13 billion to 314 billion parameters). The lower number of parameters can allow an LLM to be deployed on edge devices, e.g., NVIDIA Jetson while the larger ones require more hardware resources.

Table II shows the distribution of license categories among our listed LLM models. Regarding commercial usage of the listed LLMs, around 51% of models have permissive licenses (Apache 2.0, MIT, Gemma) that allow for commercial usage without permission from model authors. Additionally, approximately 32% of listed LLMs have limited commercial usage licenses (LLaMA-2, LLaMA-3, DataBricks Open Model License). Models with such licenses require permission from model authors if commercial usage exceeds 700M monthly active users. In Table I, such models are denoted as “Partial” commercial usage.

TABLE I. A SNAPSHOT OF THE TABLE OF CURRENT OPEN-SOURCE LLMs

Family	Name	Release Year	Size (B Parameters)	License type	Commercial Usage	Fine-tuning		Inference		
						Min. GB GPU	Min. GB RAM	Min. GB GPU	Min. GB Disk Space	
Code	Code-13B	Dec 23	13	CC-BY-NC-ND 4.0	No	26	11.73	5.4	9.23	
	Code-33B	Dec 23	33	CC-BY-NC-ND 4.0	No	66	25.55	13.5	23.05	
CodeLLaMA	7B	Aug 23	7	LLaMA-2	Partial	14	7.28	2.8	4.78	
	7B-Instruct	Aug 23	7	LLaMA-2	Partial	14	7.28	2.8	4.78	
	7B-Python	Aug 23	7	LLaMA-2	Partial	14	7.28	2.8	4.78	
	13B	Aug 23	13	LLaMA-2	Partial	26	11.73	5.4	9.23	
	13B-Instruct	Aug 23	13	LLaMA-2	Partial	26	11.73	5.4	9.23	
	13B-Python	Aug 23	13	LLaMA-2	Partial	26	11.73	5.4	9.23	
	34B	Aug 23	34	LLaMA-2	Partial	68	26.84	14.2	23.84	
	34B-Instruct	Aug 23	34	LLaMA-2	Partial	68	26.84	14.2	23.84	
LLaMA-2	7B	Jul 23	7	LLaMA-2	Partial	14	7.28	2.8	4.78	
	7B-Chat	Jul 23	7	LLaMA-2	Partial	14	7.28	2.8	4.78	
	7B-Coder	Dec 23	7	LLaMA-2	Partial	14	7.28	2.8	4.78	
	13B	Jul 23	13	LLaMA-2	Partial	26	11.73	5.4	9.23	
	13B-Chat	Jul 23	13	LLaMA-2	Partial	26	11.73	5.4	9.23	
	70B	Jul 23	13	LLaMA-2	Partial	140	51.25	29.3	48.75	
	70B-Chat	Jul 23	70	LLaMA-2	Partial	140	51.25	29.3	48.75	
Med42	70B	Nov 23	70	Med42	No	140	51.25	29.3	48.75	
Starling LM	7B-Alpha	Nov 23	7	CC-BY-NC 4.0	No	14	7.63	2.7	5.13	
	Alpha 8X7B MoE	Dec 23	47	CC-BY-NC 4.0	No	94	34.73	17.3	32.23	
WizardLM	7B-v1.0	Apr 23	7	Non-commercial	No	14	7.28	2.8	4.78	
	13B-v1.2	Jul 23	13	LLaMA-2	Partial	26	11.73	5.4	9.23	
	30B-v1.0	Jun 23	30	Non-commercial	No	60	25.55	13.5	23.05	
	70B-v1.0	Aug 23	70	Non-commercial	No	140	51.25	29.3	48.75	
Zephyr	3B	Nov 23	3	StabilityAI Non-Commercial Research Community License	No	6	4.49	1.2	1.99	
	7B-Alpha	Oct 23	7	MIT	Yes	14	7.63	2.7	5.13	
	7B-Beta	Oct 23	7	MIT	Yes	14	7.63	2.7	5.13	
BioMistral	7B	Feb 24	7	Apache 2.0	Yes	14	7.63	2.7	5.13	
	7B-DARE	Feb 24	7	Apache 2.0	Yes	14	7.63	2.7	5.13	
	7B-TIES	Feb 24	7	Apache 2.0	Yes	14	7.63	2.7	5.13	
	7B-SLERP	Feb 24	7	Apache 2.0	Yes	14	7.63	2.7	5.13	
TinyLLaMA	1.1B-Chat-v1.0	Jan 2024	1.1	Apache 2.0	Yes	2.2	3.28	0.5	0.78	

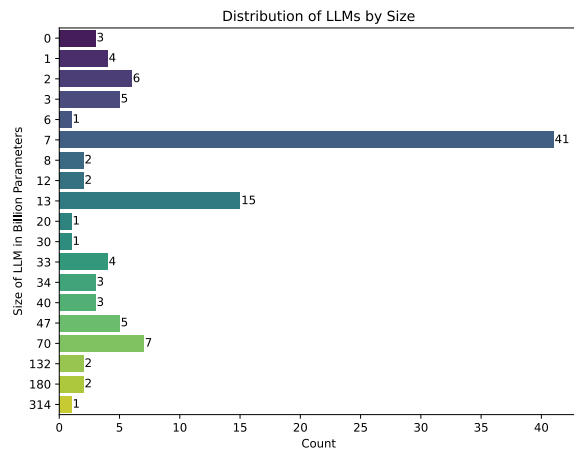


Figure 2. Distribution of LLM Size in Billion Parameters

Our comparison table includes LLMs that have been specifically fine-tuned for the medical domain. Reducing hallucinations is particularly crucial in the medical field, as the generated responses may be used for diagnosis and treatment. Consequently, medical LLMs like BioMistral, Medicine-LLM, and Meditron have been fine-tuned by their developers using textual data from PubMed Central Open Access, internationally recognized medical guidelines, and a meticulously curated

TABLE II. LICENSE DISTRIBUTION OF OPEN-SOURCE MODELS IN OUR LIST

License Type	Count	Percentage (%)
Apache 2.0	36	33.33
LLaMA-2	29	26.85
Gemma	12	11.11
MIT	7	6.48
CC-BY-NC 4.0	5	4.63
CC-BY-NC-ND 4.0	4	3.70
LLaMA-3	4	3.70
Non-commercial	3	2.78
Microsoft Research License	2	1.85
Databricks Open Model License	2	1.85
Falcon-180B TII license	2	1.85
Med42 (derivative of LLaMA-2)	1	0.93
StabilityAI Non-Commercial Research Community License	1	0.93
<b>Total</b>	<b>108</b>	<b>—</b>

medical corpus.

### V. CONCLUSION

In this paper, we proposed a comprehensive list of LLMs. This list is aimed at supporting researchers and companies in selecting LLM that is suitable for their use case, needs, and hardware requirements. This list is an ongoing effort and will be updated as new pre-trained or fine-tuned LLMs arrive.



Fine-tuning capability of LLMs has led to many derivations of them for specific use cases. Since listing every fine-tuned LLM may not help researchers and companies and on the opposite; may confuse them more, this list does not cover all the fine-tuned versions of foundational LLMs. Another limitation is that the proposed list may not include the latest LLMs since the update frequency of the table may not align with the publication of new ones.

In future work, we will include more domain-specific models to list the LLM options for different applications. Furthermore, we will assess user feedback and highlight the advantages and disadvantages of the recommended deployments. Note that, in this study, the LLMs listed were not tested. The requirements provided by HuggingFace and the developers of LLMs will be verified as part of the future work.

#### ACKNOWLEDGMENT

We thank Nehal Darwish (University of Stuttgart, Institute of Industrial Manufacturing and Management (IFF)) for preparing the first draft of the comparison list.

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