An Audit on the Perspectives and Challenges of Hallucinations in NLP

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Abstract

We audit how hallucination in large language models (LLMs) is characterized in peerreviewed literature, using a critical examination of 103 publications across NLP research. Through the examination of the literature, we identify a lack of agreement with the term 'hallucination' in the field of NLP. Additionally, to compliment our audit, we conduct a survey with 171 practitioners from the field of NLP and AI to capture varying perspectives on hallucination. Our analysis calls for the necessity of explicit definitions and frameworks outlining hallucination within NLP, highlighting potential challenges, and our survey inputs provide a thematic understanding of the influence and ramifications of hallucination in society.

1 Introduction

Recent advancements in Natural Language Processing (NLP) have expanded beyond traditional Machine Learning tools, evolving into sociotechnical systems that combine social and technical aspects to achieve specific goals (Gautam et al., 2024; Narayanan Venkit, 2023). They have now become integral in various domains such as health, policy-making, and entertainment, (Jin and Mihalcea, 2022; Werning, 2024) showcasing their significant impact on daily life. However, language models (LM) exhibit negative behaviours such as hallucination and biases (Bender et al., 2021; Gupta et al., 2024). This has catalyzed a surge in research investigating the phenomenon of hallucinations in NLP (Ji et al., 2023a), reflected in the escalating number of peer-reviewed publications on the topic, as illustrated in Fig 1, sourced from SCOPUS.

Within the NLP domain, various frameworks have emerged to define hallucination, primarily emphasizing its negative aspect. Hallucination here refers to the model's production of references to non-existent objects or statements, lacking supporting examples in the training data (Ji et al., 2023a).



Figure 1: Articles published each year (from 2013 to 2023) in SCOPUS that contain the term 'hallucination' AND ('NLP' OR 'AI') in the title, abstract, or keywords.

Despite the growing research on this topic, there is still a notable divide in our understanding, a lack of a unified framework, and a need for precise definitions (Filippova, 2020a).

The necessity to understand this gap is accentuated by research demonstrating the societal impacts of hallucinations (Dahl et al., 2024). Hence, there is a growing need to explore how the field of NLP conceptualizes hallucination. In line with this imperative, the following questions guide this study:

- **RQ1**: What are the definitions and frameworks used to explain hallucinations in NLP?
- **RQ2**: What is the current understanding of researchers about hallucinations, and how do they encounter them in their work?

To answer the RQ1, we first conduct an audit of the field of hallucinations in NLP by surveying 103 peer-reviewed articles¹. Subsequently, we conduct a survey to 171 researchers and academics in the field to gather their perspectives on this phenomenon, providing a novel contribution to the literature, addressing RQ2. By surveying NLP practitioners, the paper incorporates real-world perspectives, enriching the theoretical discussions with

¹https://github.com/PranavNV/The-Thing-Called-Hallucination

practical insights. This audit therefore aims to broaden the communities perspective by presenting practical insights from researchers employing these methods in their work. We also propose an ethical framework to guide future efforts in comprehending and mitigating hallucinations in LLMs.

2 Evolution of Hallucination in NLP

The term 'hallucination' has a long history in machine learning and has been used in various contexts prior to the LM era. Its earliest documented usage can be traced to the 2000s when Baker and Kanade (2000) applied it in the context of image resolution enhancement, referring to the generation of new pixel values. Subsequently, "hallucination" has been frequently employed in computer vision research, including notable works such as Hsu et al. (2010) on face hallucination.

In the modern deep learning era, hallucination was used first by Andrej Karpathy in his blog focusing on Recurrent Neural Networks (Karpathy, 2015). He used the term within the context of LM by illustrating how an LSTM could generate nonexistent URLs, effectively 'hallucinating' data. The term then gained major traction with the launch of ChatGPT (Wu et al., 2023), where it referred to inaccuracies and factual mistakes produced by models (Ji et al., 2023a). However, the field lacked a unified definition, leading to a spectrum of interpretations (Filippova, 2020b). In one of the earlier works, Maynez et al. (2020) divides term usage into intrinsic and extrinsic hallucination. Intrinsic hallucinations are consequences of synthesizing content using the information present in the input. Extrinsic hallucinations are model generations that ignore the source material altogether.

However, there is a rise in discussion around terminology that reflects a deeper inquiry into the phenomena, with recent discourse advocating for 'confabulation' (Millidge, 2023) or 'fabrications' (McGowan et al., 2023) as a more precise descriptor. This reflects the lack of consensus on the term and highlights the importance of looking at the use of hallucination with a more critical lens.

3 Related Surveys on Hallucination

We now provide an overview of several key surveys in the realm of NLP focusing on the topic of hallucination and why our work addresses a relevant gap in the field. Starting with Ji et al. (2023a), this survey extensively delves into the advance-

ments and challenges concerning hallucination in NLG, distinguishing between intrinsic and extrinsic frameworks of hallucination. Additionally, it sheds light on fundamental terms such as hallucination, faithfulness, and factuality, along with prevalent metrics for quantifying these phenomena. Rawte et al. (2023b) categorizes existing works within the domain of LMs, covering various aspects including methods for detecting hallucination, mitigation techniques, datasets used, and evaluation metrics. Zhang et al. (2023c) addresses the challenges of hallucination in LLMs by categorizing hallucinations into input-conflicting, contextconflicting, and fact-conflicting types, diverging from traditional viewpoints.

Furthermore, Huang et al. (2023) redefines the taxonomy of hallucination into factuality and faithfulness, with additional subdivisions, and proposes mitigation strategies aligned with underlying causes. Tonmoy et al. (2024) offer a comprehensive overview of over thirty-two techniques developed to mitigate hallucination in LLMs and finally, Rawte et al. (2023a) present a nuanced categorization of hallucination into six types, contributing to the ongoing discourse within the field.

While these surveys offer insights into the current state of hallucination research, they do not pay attention to critical examinations of the field's weaknesses arising from a lack of discourse in defining hallucination and challenges due to the same. This deficiency in discussion reflects the broader trend within the entire field. Therefore, our audit answers this gap by critically examining how we conceptualize hallucination. We aim to highlight the challenges stemming from these definitions and to further conduct a practitioner survey within the community to understand researchers' and developers' perspectives on this issue. Our goal is to facilitate a shared understanding of the challenges and mitigation strategies for hallucination and develop actionable design principles through an ethics sheet to address these issues effectively.

4 Critical Analysis of Hallucination in NLP Literature

This section is dedicated to conducting an audit of hallucination research within NLP, aiming to uncover its applications and subsequently identify the strengths and weaknesses in current literature.

To accomplish this, we conducted an audit of works from the ACL anthology using specific

NLP Tasks	Frequency	
Conversational AI	38	
Abstractive Summarization	16	
Data-to-Text Generation	14	
Machine Translation	12	
Image-Video Captioning	8	
Data Augmentation	8	
Miscellaneous	7	

Table 1: Frequency of papers reviewed for each thematically grouped NLP tasks.

keywords such as 'hallucination', 'NLP (OR) AI' AND 'hallucinations', 'fabrication', and 'confabulations'. We surveyed papers released on and before April 19th, 2024. From this search, a total of 164 papers were retrieved. After filtering out papers that were not directly related to hallucination research or those that merely mentioned the term without substantial focus on the topic, we arrived at a corpus of **103 papers**. This corpus forms the basis for our audit and analysis of hallucination research, specifically within the NLP domain.

4.1 Conceptualization of Hallucination

We performed an iterative thematic analysis (Vaismoradi et al., 2013) to uncover the various applications of hallucination research in NLP. To ensure accuracy and prevent misclassification, this recursive process was employed. This resulted in the identification of seven distinct fields that address research on hallucination (as shown in Table. 1).

This taxonomy affords insights into the pervasive nature of hallucination in NLP. Notably, it reveals that hallucination transcends beyond text generation, extending its conceptualization to encompass broader domains such as *Image-Video Captioning, Data Augmentation,* and *Data-to-Text Generation* tasks. This depicts the significance of hallucination both within and beyond the realm of NLP. Moreover, our classification framework provides us with a faceted analysis of how each of these tasks defines the concept of hallucination.

Using thematic categorization, we come across definite attributes across the definitions of hallucination. One set of attributes elucidated how hallucinations are associated with the style/language generated by the model: **Fluency**, **Plausibility**, and **Confidence**. The next set of attributes falls under the effects of hallucinations: **Intrinsic**, **Extrinsic**, **Unfaithfulness** and **Nonsensical**. The definition of each of these attributes is elaborated in Table 2.

In each paper analyzed within the survey scope, hallucination is defined based on a combination of the set of attributes identified. Our survey revealed **31 unique frameworks** for conceptualizing hallucination, illustrating the diverse approaches and perspectives used. This diversity underscores the ambiguity in the term's usage.

To illustrate this phenomenon, we present some examples showcasing the diverse approaches commonly observed in the literature:

"Hallucination refers to the phenomenon where the model generates false information not supported by the input." - (Xiao and Wang, 2021a)

"LLMs often exhibit a tendency to produce exceedingly confident, yet erroneous, assertions commonly referred to as hallucinations." - (Zhang et al., 2023a)

"Models generate plausible-sounding but unfaithful or nonsensical information called hallucinations" - (Ji et al., 2023c)

Hence, within NLP, a notable deficiency persists in grasping coherent characteristics of hallucination. This shortfall underscores the risk of potential misappropriation of the term when employed in divergent contexts. An extensive analysis of hallucination for each of the mentioned NLP tasks and its definition is illustrated in the following section.

4.2 Hallucination in NLP Tasks

We now analyze what aspects of the definitions of hallucination most commonly occur within each of our identified sub-fields of NLP^2 (Table 3).

Conversational AI: In this sub-field, hallucination encompasses fluency, non-factuality, and both intrinsic and extrinsic hallucinations. The definitions' facets highlight that dialogue systems must balance conversational fluency with factual consistency, aligning both with prior conversation and real-world truths.

Abstractive Summarization: Works in this subfield mainly focuses on extrinsic and intrinsic hallucinations in defining it. Some definitions also mention the faithfulness of the generation. Despite the challenges of aligning with real-world facts and source consistency, prioritizing alignment and adherence to the original material has been shown to be essential in these works.

Data2Text Generation: Hallucinations are classified into extrinsic and intrinsic types, similar to abstractive summarization. Here, alignment with the underlying data is emphasized as the more critical factor when compared to the language used.

²The breakdown of all the works associated with each of the subfields is in our *Appendix*.

Attributes	Definition
Fluency	The syntactic incorrectness and semantic errors of the sentence generated.
Plausibility	The degree to which the generated text
	appears factually incorrect or unbelievable within the given context.
Confidence	The absence of modifiers or qualifiers that express
	uncertainty in the generated text, presenting the output with a sense of assuredness.
Intrinsic	The generated output that contradicts the source content or the input provided
Extrinsic	The generated output that cannot be verified from the source content or the input provided.
Non-factual	Inconsistent with facts in the real world, leading to the generation of non-factual
	content in accordance to the established real-world knowledge.
Unfaithfulness	Inconsistent to the input prompt or context, creating deviations
	or inconsistencies that would diverge from the intended meaning or message.
Nonsensical	Lack of logical meaning or coherence within a given context as well as the readability of the text.

Table 2: The attributes that appear in the definitions of hallucination.

Machine Translation: Definitions of hallucination predominantly concentrate on extrinsic hallucination, with rare mentions of intrinsic hallucinations. This observation suggests a lesser concern for stylistic nuances in text generation within this field, with a greater emphasis on comprehending and conveying translated content accurately.

Image and Video Captioning: Models are expected to maintain consistency with the source while also incorporating real-world knowledge to address gaps and apply common sense. Consequently, the definition of hallucination in this context encompasses intrinsic, extrinsic, and non-factual elements, highlighting these requirements.

Data Augmentation: Works from this domain often omit explicit definitions of hallucination, indicating a divergence in emphasis or a nascent exploration of this construct within this sub-field.

Miscellaneous: Encompassing tasks such as language inference and factuality detection, this category's definitions of hallucination encompass aspects like factuality, intrinsic and extrinsic hallucination, fidelity, and nonsensicality. It's evident that within these subfields, hallucination addresses both the stylistic aspects of model output and the fidelity and accuracy of generated content.

From the analysis of different subfields, it is evident that each perceives hallucination differently, emphasizing specific attributes such as factuality, fidelity, or linguistic styles like confidence, while potentially overlooking others. This diversity indicates that hallucination as a concept is still in its early stages in the field, with various frameworks emerging and a general lack of consensus regarding its definition and application. Furthermore, the lack of social aspects in hallucination discussions in these subfields contrasts with the broader understanding and research in fields like healthcare.

4.3 Audit of Frameworks

We now scrutinize the dominant frameworks employed in defining hallucination while also assessing the extent to which these models accurately capture the phenomenon. We start by looking at *how many of the selected works explicitly define hallucination*. Out of the **103** papers, just **44** (42.7%) provide a definition of the term, leaving the majority—**59 papers or 57.3%**—either altogether omitting their understanding of hallucination in the context of their research or providing no definition or a framework. This lack of transparency is not only concerning but also underscores the need for clarity, especially given the varied interpretations of hallucination across different research domains.

Taking our scrutiny a step further, we investigate whether the works defining hallucination reference and acknowledge preexisting frameworks. It emerges that only **29 papers or 27%** of the selected works explicitly acknowledge and adhere to established frameworks of hallucination, while the remainder **73%** either loosely define the term or devise new definitions tailored to their specific research scope. This trend within the field shows a lack of consensus on the conceptualization of hallucination, leading to disparate interpretations and a shortage of discourse on the subject.

We also audit the sociotechnical nature of the definitions of hallucination in NLP. Hallucination (elucidated in Appendix 10.1) inherently contains social dimensions, creating varied perspectives across different social contexts. Moreover, given the evolution of LMs into social spaces, adopting a sociotechnical approach becomes necessary, given that the term 'hallucination' is inherently a *shared vocabulary* within these domains. Unfortunately, out of the 103 works examined, **only 3** acknowledge the this nature of hallucination, with **none** utilizing this framework to inform their approach.

Application	Definitions	Frequency	
Conversational AI	AI systems designed for natural language conversations,	38	
Conversational AI	understanding inputs, and generating appropriate responses	58	
Abstractive Summarization	Generating concise summaries by preserving main ideas		
Abstractive Summarization	and context, often creating new sentence	16	
Data2Text Generation	Automatically converting structured data into human-	14	
Data2 Text Generation	readable text, used in reporting and narratives		
Machine Translation	Automatically translating text between languages using	12	
	computational methods like neural networks		
Image and Video Captioning	Generating descriptive captions for visual content, aiding	8	
image and video Captioning	accessibility and understanding		
Data Augmentation	Techniques to increase data diversity and quality, improving	8	
Data Augmentation	model performance individual aspects of an entity		
Miscellaneous	Encompasses additional non-accomodated tasks like natural	7	
wiscentaneous	language inference and factuality detection	/	

Table 3: Frameworks of Sentiment and corresponding definitions in Sentiment Analysis

This underscores a need for research to explore the sociotechnical dimensions inherent in hallucination, showcasing the limited depth of understanding within the ML and NLP communities.

4.4 Audit of Metrics

In the analysis of the 103 papers, we observed that **87 of these works** dedicate efforts to measuring 'hallucination.' This observation depicts the prevailing trend within NLP, emphasizing the significance of quantifying the concept of hallucination across diverse research efforts. Building upon prior studies such as Ji et al. (2023a), our analysis categorizes the common approaches in NLP for quantifying hallucination into four major themes: *Statistical Metrics, Data-driven Metrics, Human Evaluation,* and *Mixed Methodologies*.





Statistical metrics calculates a hallucination score based on the degree of mismatch, with higher discrepancies indicating lower accuracy, factuality or faithfulness and hence, higher hallucination (Ji et al., 2023a). Statistical scores such as BLUE, ROUGE, and Error Rate metrics are commonly used in this approach. Our findings reveal that **35.2%** of the works that quantify hallucination opt for statistical metrics, employing **25 distinct met**- **rics** (e.g., BERTScore, F1, Perplexity, Cosine Similarity) developed for this purpose. This variability underscores the lack of a standardized approach.

Data-driven metrics utilizes curated datasets or neural models to gauge hallucination in generated text. This methodology, accounting for curated knowledge/content mismatches, is adopted by **26.1%** of the works, resulting in the development of **18 distinct** datasets or models tailored for hallucination measurement, such as CHAIR (Caption Hallucination Assessment with Image Relevance) and SelfCheckGPT (Manakul et al., 2023).

Human evaluation offers a complementary perspective by employing human annotators to assess hallucination levels, compensating for apparent errors in automated indicators (Ji et al., 2023a). This approach, used by **10.2%** of the works, encompasses scoring and comparison methods, where annotators rate hallucination levels or compare output texts with baselines or ground-truth references. Notably, one outlier paper introduced an innovative approach utilizing eye tracking for hallucination detection in NLP tasks (Maharaj et al., 2023).

Mixed method approach is deployed by 28.4% of the works, combining human evaluation with statistical metrics to offer a holistic perspective on hallucination quantification. This trend reflects a concerted effort within the research community to address the limitations of individual methodologies and provide insights into the presence and nature of hallucination in generated texts.

The metrics audit reveals significant knowledge gaps and challenges across various approaches. Notably, established research highlights areas for improvement in standard methods for measuring hallucination. For instance, methodologies like CHAIR and metrics such as ROUGE scores exhibit instability in measuring hallucination due to the need for complex human-crafted parsing rules for exact matching, rendering them susceptible to errors (Li et al., 2023). Criticisms also extend to human evaluation methods, which are prone to inaccuracies in gauging hallucination within these models (Smith et al., 2022).

Beyond methodological criticisms, our audit uncovers a trend of employing numerous distinct metrics and approaches within these frameworks to categorize hallucinations. Over time, this has led to a diverse set of parameters for measuring hallucination, with a general lack of consensus on a standardized measurement approach. This issue further highlights the absence of a unified method, especially as these models have now shifted to become a sociotechnical solution (Bender et al., 2021).

5 Practitioner Survey of Hallucination

In this section, adopting a 'community-centric approach' (Narayanan Venkit, 2023), we conduct a survey to gain insights into researchers' perceptions of hallucinations in NLP to complement our theoretical discussions with practical real-world perspectives. The primary goal is to demonstrate how researchers and practitioners within the field perceive the concept of 'hallucination' and to expand our findings beyond the limitations of existing literature where real-world perceptions from the researchers are missing (Huang et al., 2023; Zhang et al., 2023c; Ji et al., 2023a). This motivates us to gather real-world perspectives from individuals actively engaged in NLP and AI research.

5.1 Survey Recruitment and Data Collection

For our survey, we employed a multi-faceted approach to reach a diverse population of respondents. We utilized direct emails, direct messages, and social media platforms such as LinkedIn and Twitter to distribute the survey. Our target audience included graduate students and professors from academic backgrounds as well as individuals from the industry who work in NLP, aiming to capture a wide range of perspectives on hallucinations.

To ensure a comprehensive view, we specifically targeted researchers familiar with AI and ML, primarily from disciplines such as computer science and information science. However, we also welcomed participants from other domains to explore their perceptions of whether they had the literature understanding of the concept of hallucination as they are also extensively using LLM models. The survey was examined and approved by the Institutional Review Board (IRB) for ethical practices.

We additionally employed a systematic approach by randomly selecting 15 universities from the top 100 in the USA as per the 2023 US News and World Report rankings (News, 2023), to then reach out to potential participants. Prior works (Chakravorti et al., 2023) have previously employed this process to identify high-quality participants. We received a total of 223 responses, out of which 171 were complete and usable for analysis.

5.2 Survey Structure

The survey employed a combination of 14 openended and close-ended questions. The survey has been built based on the previous survey design techniques (Rosen et al., 2013; Baker, 2016; Van Noorden and Perkel, 2023; Chakravorti et al., 2024). Open-ended questions and free-response text boxes allow us to gather rich opinions from participants. This approach integrates all our findings, providing a broader and deeper understanding of the response. For the analysis of open-ended questions, we utilized thematic analysis, drawing from established methodologies outlined in Blandford et al. (2016); Terry et al. (2017). The close-ended questions were analyzed using descriptive statistics to summarize and analyze the numerical data obtained from respondents. Throughout the analysis process, the research team made collective decisions regarding the retention, removal, or reorganization of themes derived from open-ended responses. All the survey questions have been provided in Appendix 10.3.

5.3 Survey Findings

We now summarize insights from our responses to explore various perspectives on hallucinations in LLMs, including perceptions, weaknesses, and preferences. The breakdown of responses indicates that 76.54% of participants were from academia, 20.98% from the industry, and 2.47% both.

Participants were also asked about their research area's direct relation to AI and NLP. The analysis revealed that more than 68.52% of researchers indicated that their work is directly related to NLP, while the remaining respondents either exhibited familiarity with or indirectly incorporated NLP and AI methodologies in their work. This highlights the substantial involvement of AI experts and practitioners within the survey.



Figure 3: Respondents familiarity with 'Hallucination'

5.3.1 Familiarity with Hallucination

The survey included the question on participants' familiarity with the concept of 'hallucinations' in AI-generated text, measured on a 5-point Likert scale. The analysis revealed that 24.07% of researchers reported being extremely familiar with the concept, while 33.33% indicated being very familiar with it (Figure 3). Participants who indicated not being familiar with the term 'hallucination' (7.96%) also demonstrated implicit concerns with this phenomenon by highlighting issues such as generating incorrect responses and crafting stories autonomously. This demonstrates the widespread impact of the phenomenon within the community.

5.3.2 Hallucination Frequency

The survey included a question regarding the frequency of encountering 'hallucinated' content, defined as content that is factually incorrect or unrelated to the input, assessed on a 5-point Likert scale ranging from 'Never' to 'Very frequently' (Figure 4). The analysis revealed that 46.91% of respondents reported encountering hallucinated content occasionally, while 29.01% indicated experiencing it frequently. The results suggest that a substantial portion of practitioners encounter instances of hallucinated content in AI-generated outputs, indicating a prevalent issue in generative NLP models.



Figure 4: Frequency of encountering 'Hallucination'

5.3.3 Perceptions of Hallucination

The survey findings revealed that **more than 92%** of respondents perceive hallucination as a weakness of LLMs. Subsequently, participants were asked to provide their own definitions of 'hallucination' in generative AI models through an openended question. To analyze these responses, we applied thematic categorization based on attributes generated from the literature audit (Table 2).

The thematic categorization revealed that the majority of respondents categorized hallucination as pertaining to the *factuality and faithfulness of input*, *with relatively lesser emphasis on the extrinsic and intrinsic nature of hallucination* concerning the input. This trend reflects a common perception of how hallucination is understood within the context of larger-scope generative AI models.

Moreover, the analysis identified **12 distinct frameworks** regarding how hallucination is defined by respondents. For example:

"Response that appears syntactically and semantically believable, but is not based on actual fact"— Academic Researcher, NLP

"When the model confidently states something that is not true"—Academic Researcher, AI

The diversity of viewpoints underscores the inconsistency within the field regarding the conceptualization and understanding of hallucination in the context of generative AI models.

5.3.4 Alternative Terms for Hallucination

The survey included a question asking participants if they prefer an alternate term to describe the phenomenon of 'hallucination' in AI-generated content and to provide an explanation if they do. The analysis revealed that 54.32% of respondents preferred the term hallucination or had no other term to provide. However, among the remaining responses, **40.46%** of participants mentioned **'Fabrication'** as a better term to describe the phenomenon.

This indicates that while the majority of respondents did not propose an alternative term, a notable proportion sees fabrications as a more suitable descriptor for the phenomenon of hallucination in AI-generated content. For example,

"Fabrication makes more sense. Hallucination makes it feel like AI is human and has the same sensory perceptions that could lead to hallucinations."—Academic Researcher, AI & Education

It's interesting to note that a few researchers also prefer to use the term **'Confabulations'** instead of 'hallucinations' when referring to AI-generated content. Their rationale likely stems from the nuanced difference in meaning between the two terms. While hallucinations generally convey the idea of perceiving something that is not based on reality or fact, confabulations specifically refer to the creation of false memories or information without the intention to deceive.

By opting for the term 'Confabulations,' researchers may be emphasizing the unintentional nature of the inaccuracies or false information generated by AI models, as opposed to implying deliberate deceit. For example,

"I think confabulation works better because it means creating a false memory without deceit. Fabrication gives the idea that it is intentional, which in the case of generative AI models, it is not."— Academic Researcher, AI & HCI

It's also insightful to see that respondents proposed various alternative terms to describe the phenomenon of hallucination in AI-generated content such as *incorrect information/misinformation*, *Non-factual information, Cognitive gap, hypergeneralization, Overconfidence,* and *Randomness.* These alternatives highlight different aspects and nuances of the inaccuracies or distortions present in the generated content. Participants also mentioned how they prefer multiple terms based on the application in which they are used.

"As I mentioned there are different types of hallucinations. For instruction and context hallucinations, I would refer to them as inconsistency instead. For factually incorrect hallucinations, the word hallucination is fine."—Academia, NLP

5.3.5 Creativity and Positive Applications

Not all researchers view hallucinations in AIgenerated content through a negative lens. While the majority may associate hallucinations with inaccuracies or distortions, a notable minority ($\sim 12\%$ in our survey) provided insights into how they believe hallucinations in these models can be correlated with creativity rather than negatively impacted behaviors. In fields such as story narration and image generation, researchers often value the creative behaviors exhibited by AI models. Hallucinations, when viewed in this context, may be seen as manifestations of the model's ability to think outside the box, generate novel ideas, and explore unconventional possibilities. These creative outputs can inspire new approaches to storytelling, art, and problem-solving, contributing to innovation and artistic expression. For example:

"Hallucinations are just what is needed for models to be creative. In truth, unless AI text-generators are factually grounded with external knowledge for a specific field, they are just story generators which aim to be creative, hence "hallucinate.""— National Lab Researcher, NLP

Further supplementary analysis and quotes on the various external perspectives and the societal ramifications of hallucination, obtained through the survey, is examined in the *Appendix 10.2*.

6 Challenges and Recommendations

Based on our audit and survey analysis, we outline the key weaknesses encountered in hallucination within NLP and potential recommendations motivated by the weaknesses. We utilize a communitycentric approach to define the primary weaknesses of the field currently and a path forward.

6.1 Challenges

The primary challenges we identify thematically and aim to elucidate are as follows:

Wide range of vague and absent definitions: The literature and the practitioner's survey show diverse and conflicting frameworks, often lacking clarity or omitting explicit definitions for hallucination and how it is perceived in various fields of NLP and language generation. Ambiguity arises from the use of terms like 'confabulations,' ' fabrications,' 'misinformation,' and 'hallucinations' interchangeably, without clear definitions in the context of hallucinations.

Lack of standardization in measurement: The absence of standardized metrics to quantify hallucination results in the use of multiple scales and categorizations. This makes it challenging to compare and interpret results across different models and studies, leading to a proliferation of diverse approaches for evaluating hallucinations.

Limited awareness of hallucination in a sociotechnical context: Hallucination research often lacks the understanding of how the concept of hallucination is conceptualized beyond its technical purview. When such analysis is employed in sociotechnical systems like healthcare and policy making (Dahl et al., 2024; Pal et al., 2023), it is important to define the socially relevant framework of hallucination as well.

Multiple sentiment towards hallucination: The perception of hallucination in generative AI varies depending on the context. For instance, it is often positively regarded as creativity in image generation, whereas in text generation, it is viewed negatively as errors or mistakes. Consequently, future research efforts should aim to better address this disparity to develop a more nuanced framework for understanding hallucination.

Lack of standardized nomenclature: Both our literature audit and practitioner survey revealed that the term 'hallucination' is inadequate to fully capture the behavior exhibited by NLG models. There is a need for further investigation into which terms are more appropriate and why they are necessary. For instance, terms like 'confabulation,' 'fabrications,' and 'misinformations' are increasingly being used to describe the same phenomenon. A more precise understanding is required to distinguish between these terms and how they are utilized in various fields within NLP.

User trust and reliability: Our survey findings suggest that users may hesitate to fully utilize LLM capabilities due to concerns about bias and hallucination despite recognizing the potential advantages these models offer. Therefore, there is a need to focus efforts on understanding the human interaction aspect concerning hallucination in NLP and language generation.

Addressing these issues requires careful consideration of the categorization approach, integration of contextual information, and, efforts towards robust evaluation methodologies in hallucinations.

6.2 Recommendations

Expanding on audits like Blodgett et al. (2020) & Venkit et al. (2023), we examine strategies for NLP practitioners studying 'hallucination' to overcome these challenges. We propose two overarching themes with four associated recommendations.

Author-Centric Recommendation. These recommendations prioritize actionable steps for both the author and developers, emphasizing transparent and accountable development in conceptualizing hallucinations.

[R1] Ensure explicit documentation of the hallucination framework and analysis methodology employed during the development of NLP models. Provide guidelines that outline the expected measurements and quantifications for the model to enhance interpretability and applicability.

[R2] Explicitly state the use cases and user profiles intended to interact with the NLP system. By considering the specific applications and targeted users, it is easier to construct the required framework of hallucination that is sensitive to the community in consideration. Raise awareness about potential ramifications introduced by NLP models, emphasizing the importance of fairness and equity.

Community-Centric Recommendation. These recommendations prioritize actionable steps for the research community to enhance frameworks and understanding related to hallucinations.

[R3] Develop clear and standardized definitions for terms such as 'confabulations,' 'fabrications,' 'misinformation,' and 'hallucinations' within the context of NLP. Establish frameworks that provide clarity and consistency in understanding these concepts, particularly regarding hallucinations. This requirement is crucial due to the widespread misunderstanding of hallucination and the misnomers that have arisen as research progresses.

[R4] Promote the creation of methods that offer visibility into the model's decision-making process, enabling users to comprehend how hallucinations or fabrications can occur within the system, thus fostering trust in its use. Facilitating research discussions for transparency through workshops and conferences is one approach to achieving this goal.

7 Conclusion

Our work delves into the conceptualization of hallucination within the scope of NLP. Our approach involved two key methodologies: first, an exhaustive audit of 103 peer-reviewed papers in the NLP domain, and second, a practitioner survey of 171 researchers to complement our first study with realworld practical perception and understanding of hallucination as a unique contribution. Through this analysis, we have gained insights into how the NLP community conceptualizes and defines hallucination, showcasing a lack of discourse and agreement. Additionally, our thematic and community-based approach highlights potential weaknesses within the field, particularly in addressing misrepresentations and inaccurate characterizations associated with hallucination, paving way for better advancement in language generation. Our work finally contributes to a deeper understanding of the challenges and gaps in research related to hallucination within NLP, paving the way for future advancements in NLP and language generation.

8 Limitations

Our study encompasses a selection of 103 papers, incorporating works from primarily the ACL Anthology. While our intention was not to provide an exhaustive collection of all published works on hallucination, we aimed to include diverse sources within NLP that cover various aspects of the field. Our intent was to curate peer-reviewed literature commonly found in the NLP domain, encompassing models, applications, survey papers, and frameworks. We, therefore, did not scope the utility of hallucination and its impact beyond NLP to other fields of research, such as Computer Vision. Regarding the creation of the challenges and recommendations, it is important to note that the themes presented are not meant to be exhaustive but rather serve as a foundational framework to spark additional inquiries and foster further engagement.

Our survey was designed to capture the viewpoints of researchers and practitioners in the AI and ML field, potentially limiting various experiences. As such, our analysis is centered on this perspective. While we did gather additional insights from participants outside this field, our focus was not comprehensive in that regard. Our future work intends to explore the public's perspective on hallucination.

9 Ethics Statement

We are aware of the ethical considerations involved in our research and have taken measures to ensure responsible practices throughout the study.

Data Publication: All the papers used in our research are listed in the Appendix. However, we recognize the importance of transparency and accountability. Therefore, we publish the complete collection of papers along with our qualitative classification and annotation, allowing for public scrutiny and examination ³.

Mitigating Qualitative Bias: We acknowledge the potential for bias when performing qualitative coding of the papers regarding their applications. To address this concern, we ensured that at least three different individuals independently reviewed and verified the coding to minimize the possibility of misclassification. Additionally, we followed the same approach to verify the presence of various definitions in each paper, enhancing the reliability and validity of our analysis. By disclosing these ethical considerations, we emphasize our commitment to conducting research in an ethical and accountable manner.

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³https://github.com/PranavNV/The-Thing-Called-Hallucination

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10 Appendix

10.1 Social Perspectives on Hallucinations

The exploration of hallucination in NLP is solely technocentric; however, its conceptual roots and applications are deeply intertwined with societal interpretations. To gain a better understanding of the term 'hallucination,' it is important to consider its broader usage and implications beyond NLP. Hallucination has been studied across disciplines like psychology and neurology (Steele, 2017; Legault, 2020). Essentially, hallucinations involve "perceptions arising in the absence of any external reality – seeing or hearing things that are not there" (Steele, 2017). Although a version of this definition is commonly used in NLP, often with negative connotations, hallucinations have a wide scope, originating from fields such as neurology, and philosophy.

Hallucination and Medicine: Hallucination is believed to have neurological origins, often emerging from induced states such as drug usage, psychosis, sensory deprivation, or migraines (Legault, 2020). These experiences can encompass various sensory modalities like auditory, visual, olfactory, tactile, gustatory, or somatic sensations (Boeving, 2020). Modern neurological research like Legault (2020) suggests that while hallucinations may not align with external reality, they are linked to brain regions responsible for processing perceptions from the external world.

Hallucination and Creativity: Studies exploring hallucination in the context of creativity suggest that individuals with mild hallucinatory experiences may demonstrate enhanced generative creativity (Fink et al., 2014; Mason et al., 2021). Another prevalent notion is the use of hallucinations as a gateway to accessing intuition, creativity, and novel modes of thinking (Mason et al., 2021). However, there is a call for greater empirical rigor to establish robust connections between specific mental states leading to hallucinations and the creative thinking process (Fink et al., 2014).

The analysis of differing perspectives on hallucination reveals its diverse interpretations, challenging prevalent assumptions within NLP. However, using the term 'hallucination' without its social context can foster misconceptions. Firstly, the 'hallucinations' in AI systems result from discrepancies in input data and prompts rather than an absence of external senses. Secondly, this metaphor risks perpetuating stigma by linking negative AI phenomena with specific mental illness aspects (Pal et al., 2023), potentially hindering destigmatization efforts in mental health domains (Maleki et al., 2024). Lastly, given the widespread use of machine learning models, especially in medical fields (Ji et al., 2023c), a limited grasp of 'hallucination' context may lead to terminology misinterpretations.

10.2 Supplementary Survey Analysis

10.2.1 Weaknesses of LLM

Before delving into inquiries about hallucinations in LLMs, it is crucial to gain insights into the perceived weaknesses of these models from the participants' perspective, as well as understand how frequently they utilize these models in their work.

The survey results indicate that a significant portion of researchers heavily utilize LLMs in their daily life. Specifically, 67.28% of respondents reported using these models atleast once a day, while 20.37% mentioned using them all the time, highlighting the ubiquity of these models.

Upon analyzing the themes derived from participants' responses on the *weaknesses of generative AI tools*, it was observed that a substantial majority (55%) of researchers perceive the main weaknesses to be the generation of misinformation and hallucinations, despite both phenomena being essentially similar in nature. For instance,

"I have been exploring these models to see what they get right and wrong. They get a lot of things wrong – what some people call "hallucinations"."—Emeritus Professor, NLP

Some of the other important weaknesses mentioned by the respondents are: biases, not following the prompts correctly, complex language, and not having a long memory. For example,

"They produce a lot of inaccurate replies with great confidence. These models also tend to be very biased toward many socio-demographic groups."— Graduate student, GenerativeAI

"It is hard to distinguish whether the information provided by them is accurate or not. Sometimes, the models generate text with reasoning making it sound convincing enough to be true - but ends up being incorrect ultimately."—Industry, GenerativeAI

The responses highlight a critical concern within the research community regarding the reliability and accuracy of outputs generated by LLMs, with potential implications for various applications and domains, providing us with a strong motivation behind this study.

The widespread use of LLMs, particularly prominent models such as GPT 3, 3.5, and 4, highlights their importance and impact on research and industry practices. However, it's noteworthy that respondents also mentioned other LLM models that they use or are familiar with. These include Mistral, BERT, LLaMA2, Midjourney, ClaudeAI, Gemini, Vicuna, t5, Falcon, PaLM, Imagen, Dolly, Perplexity, among others.

10.2.2 Social Ramifications of Hallucination

Participants were prompted to explain the effects of hallucination on their work/daily life. The resulting themes, from our qualitative analysis of their inputs, are outlined below:

Not Good for Education: Respondents raised concerns about the extensive use of these models by students for homework, indicating potential negative impacts on their performance and learning abilities. The respondents believe that such reliance on these models can lead to a degradation in students' learning. Additionally, respondents express skepticism about the suitability of these models for checking homework assignments.

"I don't actually use AI for my work; I just want to be aware of what it can do because my students are probably using it for their homework. It could have an impact on students' mastery of the material."—Associate Prof, Biotechnology

Not Good for Scholarly Work: Several respondents noted that these models are not effective for scholarly purposes, citing instances where the models generated information that was not present in the original paper. They express concerns that if researchers rely on these models for tasks like literature summarizing, it could lead to a deterioration in scholarly processes. For example:

"They tend to generate a lot of misinformed facts about certain groups or cultures that I have seen happen often. They also generate 'facts' from scholarly works where the papers would not have mentioned the same."—Graduate student, NLP

Struggle with Code Generation: The models were deemed inefficient for code generation by multiple respondents, often producing code that lacks utility due to hallucinations. Respondents highlighted mismatches between the generated code and its intended purpose, emphasizing the need for thorough review before utilization. Various concerns were raised, including the loss of context during prolonged interactions, inaccuracies in complex coding tasks leading to erroneous outputs, fabrication of functions or attributes, inaccuracies in both code and associated theoretical concepts, necessitating extensive debugging and corrections, and a tendency to cycle back to previously incorrect suggestions despite error notifications.

"I was asking an AI to generate me a piece of code. It ended up picking some code from one website and some from another and combining it. However those two websites (they were linked by chatgpt) we're using different versions of the library so the resulting code couldn't be executed."— Industry, Network and Security

Increase in Time for Task: A common sentiment among respondents is that these models frequently produce errors or false information, resulting in potential time wastage. While they acknowledge occasional helpfulness, there's a consensus that reliance on these models can often lead to unfavorable outcomes, particularly when verifying outputs. This dependency on verification contributes to increased task duration, adding extra work and time toward the project's conclusion, as noted by several respondents.

"I use GPT API to conduct analysis for some of my work and accuracy and consistency would be good in my context, and I have to find ways to finetune it before I can trust the results of the analysis, which added more work on my end."— Graduate Student, HCI

Misleading and Distrust: Generating incorrect outputs with confidence can lead to the dissemination of non-existent knowledge, such as misleading information in the literature that may confuse individuals with incorrect concepts. Most of our respondents mentioned this concern. Moreover, it poses challenges in differentiating between accurate AI responses and hallucinations, particularly for users lacking expertise in the relevant subject matter.

"It leads to problems if even I do not have any idea about the work. It is hard to differentiate if it is a genuine output or hallucination."—Graduate Student, Data Science



Figure 5: Frequency of Text Generation Model Usage

10.2.3 An External Viewpoint

Additionally, our survey of 51 researchers who do not specialize in AI revealed that all except 3 have used text-generation models like various versions of ChatGPT. Despite their fields not being directly related to AI, a significant number integrate these tools into their workflow, with 19.6% using them multiple times daily and 11.76% using them several times per hour. Their extensive usage has allowed them to identify several limitations in the models; they are: *mathematical inaccuracy, outdated information, misinformation, poor performance with complex tasks and creative thinking, lack of specificity in-depth, overconfidence, lack of transparency, bias,* and *irrelevant responses.*

Based on the definitions provided, it is observed that there is a lack of clarity among the respondents regarding what constitutes a 'hallucination' in generative AI models, with perspectives varying widely. Thematic analysis of their responses indicates that the predominant view associates 'hallucination' with *the generation of nonfactual content and misinformation by AI systems*. That means these models are generating facts that are not real and misleading. The remaining themes are factually incorrect, biased outputs, incompleteness, misinformation with confidence, and nonsensical but good-looking texts. The results demonstrate the unclear comprehension and significance attributed to hallucination in LMs beyond the field of NLP and AI. There is a pressing need to enhance public understanding of the concept of hallucination, emphasizing its meaning and strategies for mitigation. Given the increasing prominence of LMs as sociotechnical systems (Narayanan Venkit, 2023), it is crucial to grasp their social interactions and potential societal ramifications.

10.2.4 Additional Impacts and Concerns

We analyzed perceptions when participants were asked about any additional concerns during the survey. Participants emphasized the necessity for greater control and more nuanced mechanisms to address and manage AI hallucinations effectively. Presently, the detection and rectification of hallucinations rely heavily on meticulous human review, highlighting the need for tools designed specifically to identify and mitigate such occurrences. The presence of hallucinations can significantly impact the credibility and acceptance of generative models among the general public. These issues arise due to the inherent limitations of generative algorithms and the absence of access to real-time external knowledge.

Transparency regarding the limitations of generative AI is deemed essential through our findings, and user education is seen as a key factor in mitigating risks associated with the unchecked use of AI-generated content, as the responsibility for identifying hallucinations often falls on the user. While inaccuracies in non-critical applications, like movie suggestions, may be tolerable, according to our survey, they are deemed crucially problematic in contexts such as business decision-making, law, or health (Dahl et al., 2024).

10.3 Survey Questions

In this section, we provide the content and the questions that were presented in the survey:

Survey Title: Insights of Usage and Issues with Text Generative Models and Tools

- 1. How did you receive the survey? (Social Media Posts, Direct email, Direct messages, Others)
- 2. What is your current country of residence? *(Open-ended)*

- 3. What sector do you associate with? (Academia, Industry, Others)
- 4. What is your field of expertise? (Open-ended)
- 5. Does your research work directly involve studying or developing Artificial Intelligence (AI)? (*Yes, No*)
- 6. How often do you use Text generation models (like ChatGPT/Gemini)? (All the time, Several times an hour, once an hour, several times a day, Once a day, Several times a week, once a week, Several times a month, Once a month, Never)
- 7. Which text generation models have you used, if any? (*Open-ended*)
- 8. What weaknesses do you perceive in the models that you have used(if any)? (*Open-ended*)
- 9. Are you familiar with the concept of 'hallucinations' in AI-generated text? (*Extremely familiar*, Very familiar, Moderately familiar, Slightly familiar, Not at all familiar)
- 10. What, according to you, is 'hallucination' in generative AI models?(*Open-ended*)
- 11. Do you consider 'hallucinations' to be a weakness when using these models? (*Yes, No*)
- 12. How frequently do you encounter that text generation models produce 'hallucinated' content that is factually incorrect or unrelated to the input? (*Very frequently, frequently, Occasionally, rarely never*)
- If you have an alternate term in mind to describe the phenomenon instead of 'hallucination' (e.g., fabrications, confabulations, etc.), kindly specify it along with an explanation(Mention NA if none). (Open-ended)
- 14. Can you provide an example where a hallucination in text generation had or can have an impact on your work (Mention NA if None)? (Open-ended)
- 15. Do you have any additional comments or insights regarding the hallucination? (if any) (*Open-ended*)

10.4 Works and Application

We illustrate the examples and categories of works that were looked into for understanding the various applications of hallucinations. We categorize the research on hallucinations into 7 major categories. The definitions and categories of all the applications are mentioned in Table 3.

Abstractive Summarization: Zhang et al. (2019); Son et al. (2022); Maynez et al. (2020); Choubey et al. (2023); Cao et al. (2021); Marfurt and Henderson (2022); Akani et al. (2023); van der Poel et al. (2022); Chen et al. (2023b); Dong et al. (2022); Shen et al. (2023); Nan et al. (2021); Chen et al. (2021); Ladhak et al. (2023); Nan et al. (2021); Flores and Cohan (2024)

Conversational AI: Liu et al. (2022); Zhou et al. (2020); Ji et al. (2023b); Zhang et al. (2023b); Yang et al. (2023); Das et al. (2022); Bouyamourn (2023); Sun et al. (2023); Sadat et al. (2023); Slobodkin et al. (2023); Ramakrishna et al. (2023); Xiao and Wang (2021b); Shuster et al. (2021); Nie et al. (2019); Longpre et al. (2021); Dziri et al. (2022); Maheshwari et al. (2023); Ladhak et al. (2022); Xu et al. (2023); Chen et al. (2023a); Goldberg et al. (2022); Sundar and Heck (2023); Roller et al. (2021); Mielke et al. (2022); Roller et al. (2021); Massarelli et al. (2020); Weller et al. (2024); Smith et al. (2022)

Data Augmentation: Jian et al. (2022); Ji et al. (2023b); Friedl et al. (2021); Samir and Silfverberg (2022); Anastasopoulos and Neubig (2019); Narayanan Venkit et al. (2023)

Image and Video Captioning: Xiao and Wang (2021b); Dai et al. (2023); Rohrbach et al. (2018); Li et al. (2023); Testoni and Bernardi (2021); Son et al. (2022); Dai et al. (2023); Li et al. (2023); Liu and Wan (2023)

Machine Translation: Wang and Sennrich (2020); Raunak et al. (2021); Dale et al. (2022); Guerreiro et al. (2023a); Xu et al. (2023); Pfeiffer et al. (2023); Guerreiro et al. (2023b); Dale et al. (2023); Irvine and Callison-Burch (2014); Ferrando et al. (2022); Vu et al. (2022); Müller et al. (2020); Waldendorf et al. (2024)

Data2Text Generation: González Corbelle et al. (2022); Shi et al. (2023); Yoon et al. (2022); Filippova (2020b); Kothyari et al. (2023); Lango and Dusek (2023); Cirik et al. (2022); Fei et al. (2023); Obaid ul Islam et al. (2023); Qiu et al. (2023); Testoni and Bernardi (2021); González-Corbelle et al. (2022); Islam et al. (2023); Polat et al. (2023) **Miscellaneous:** Manakul et al. (2023); Ji et al. (2023d); Maharaj et al. (2023); McKenna et al. (2023); Pal et al. (2023); Zhao et al. (2023); Berbatova and Salambashev (2023); Wu et al. (2024)