

Have LLMs Made Active Learning Obsolete? Surveying the NLP Community

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Abstract

Supervised learning relies on annotated data, which is expensive to obtain. A longstanding strategy to reduce annotation costs is *active learning*, an iterative process, in which a human annotates only data instances deemed informative by a model. Large language models (LLMs) have pushed the effectiveness of active learning, while also advancing methods such as few- or zero-shot learning, and text synthesis—all of which can reduce the need for active learning. This naturally raises the question: *has active learning become obsolete?* To answer this fully, we must look beyond literature to practical experiences. We conduct *an online survey in the NLP community* to collect previously intangible insights on the perceived relevance of data annotation, particularly focusing on active learning, including best practices, obstacles, and future prospects. Our findings show that annotated data is expected to remain a key factor and active learning to stay highly relevant while benefiting from LLMs. Consistent with a community survey from over a decade ago, however, we find that three key challenges persist—setup complexity, risks in the cost reduction, and tooling—for which we propose alleviation strategies. We publish an anonymized version of the collected dataset.¹

1 Introduction

Supervised learning is one of the most common concepts in natural language processing (NLP). By definition, the approach depends on annotated data, which is usually time-consuming to create and therefore expensive, making supervised learning a resource-intensive process. A longstanding strategy for minimizing the annotation effort while maintaining model performance is *active learning* (AL; Lewis and Gale, 1994), where a human annotator iteratively provides labels for small batches of data instances deemed informative by a model.

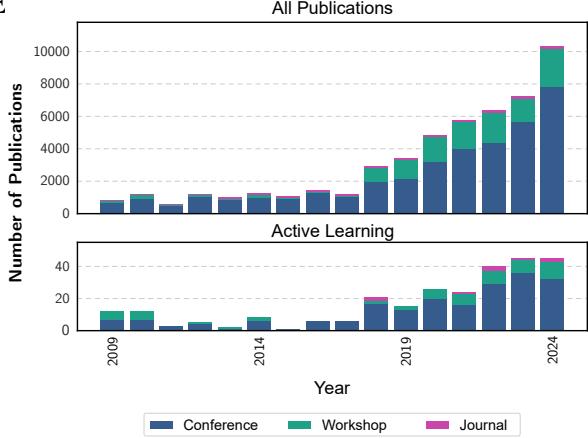


Figure 1: Comparison of total publications and AL publications in *CL conferences, workshops and journals since 2009 (see Appendix A for methodological details).

While AL is continuously researched, its primary goal is to enable practical applications. In a previous survey, Tomanek and Olsson (2009) found that only 20% of the inquired NLP practitioners had used AL to support annotation, although many were aware of it. Skepticism about practical effectiveness was cited as a key barrier. Since then, large language models (LLMs)² have irrevocably transformed NLP, considerably reducing the amount of required annotated data through the pre-training fine-tuning paradigm. Still, obtaining annotated data remains a challenge. The gains brought about by LLMs have in turn also advanced AL, and contemporary work has found considerable improvements when integrating LLMs with AL (e.g., Ein-Dor et al., 2020; Margatina et al., 2021; Tonneau et al., 2022; Yuksel et al., 2022; Xiao et al., 2023; Nachtegael et al., 2023b). Using LLMs as backbone model has generally been described as highly effective and sample-efficient, potentially resolving earlier concerns about AL’s practical benefits.

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¹Dataset will be published soon. ^{*}Equal contribution.

²We adopt the definition of LLMs from Rogers and Lucioni (2024), which encompasses both encoders and decoders.

In parallel, alternative methods to overcome a lack of annotated data have likewise benefited, such as zero-shot learning (Gilardi et al., 2023), few-shot learning (Brown et al., 2020), and text synthesis (Radford et al., 2019). This leads us to ask: *have LLMs increased the practicality of AL, or have LLMs and associated advancements made it obsolete?* The literature presents a mixed picture in this regard, as shown in Figure 1. An analysis of AL publications in *CL venues over the past 15 years reveals notable surges in 2018 and 2022, likely related to the emergence of transformer-based language models and the growing interest in generative AI. However, despite these increases, the overall number of AL publications remains low.

Regardless, drawing from the literature alone cannot provide a clear answer to this question, as the practical utility of AL—its intended purpose—is oftentimes not documented publicly. Therefore, to gain insights beyond scientific publications, we devise and conduct an extensive community survey. We collect data on (1) how the underlying problem of a lack of annotated data in supervised learning is approached in the era of LLMs, (2) reasons for or against using AL, (3) commonly used AL setups, and (4) how AL could and should be shaped in the future. The early survey by Tomanek and Olsson (2009) serves as a point of comparison, with a particular focus on the caveats identified back then.

Contributions (1) We collect a dataset of insights on annotated data and AL from the NLP community (researchers and practitioners) through a comprehensive survey with 52 questions. (2) We evaluate the responses of 144 participants both quantitatively and qualitatively, and compare them to the community report from 15 years ago. (3) We discuss the results, connect them to literature, and make predictions for expected future developments in AL. (4) We identify three key problems and outline possible solutions to ensure AL remains a preferable choice for data-efficient annotation.

Findings Our descriptive analysis shows, among other findings, that annotated data likely remains important and at the same time a bottleneck for supervised learning. Most respondents consider AL to be an effective method to address this issue; however, key challenges in AL already identified over a decade ago persist, including the complexity of setup, non-guaranteed cost reduction, and a desire for improvement of annotations tools.

2 Related Work

Components and variables in active learning

AL consists of several components (Settles, 2009): *Query strategies* (Fu et al., 2013) determine the instances to be annotated next (usually by a *human annotator*) in interaction with the *model*, which is then iteratively updated on these instances to optimize task performance. Crucial for efficiency, the *stopping criterion* (Vlachos, 2008; Laws and Schütze, 2008; Olsson and Tomanek, 2009) aims to identify appropriate termination points of the whole process. The list of variables that can influence the performance of AL is non-exhaustive and includes, among others, data properties or annotator expertise (e.g., Margatina and Aletras, 2023).

Active learning in the era of LLMs The integration of LLMs and AL has been associated with a number of benefits. Among these are the outstanding performance of LLMs that can be boosted through AL even in demanding real-world data scenarios (Ein-Dor et al., 2020), resulting in a significant reduction of human annotation effort (Shelmanov et al., 2021; Zhao et al., 2020)³, the additional source of information that pre-training provides in the cold-start of AL (Yuan et al., 2020), and capabilities such as few-shot learning (Margatina et al., 2023; Bayer and Reuter, 2024) and prompt-based strategies (Li et al., 2024). Recent studies further suggest to entirely replace the human annotator with LLMs as cost-effective alternatives (Xiao et al., 2023; Zhang et al., 2023; Kholodna et al., 2024; Liang et al., 2024). In AL research, LLMs have thus become the standard backbone models across tasks such as text classification (Ein-Dor et al., 2020; Yuan et al., 2020; Margatina et al., 2021; Galimzianova and Sanochkin, 2024), sequence tagging (Shelmanov et al., 2019, 2021; Luo et al., 2023), text summarization (Tsvigun et al., 2022a; Li et al., 2024; Xia et al., 2024) and machine translation (Zeng et al., 2019; Zhao et al., 2020; Mendonça et al., 2023; Yüksel et al., 2023).

Prior literature surveys AL for NLP has substantially grown since its beginnings. Advancements have been reviewed over time, focusing either on the overall picture (Olsson, 2009; Zhang et al., 2022), or on certain sub-aspects such as deep neural networks and text classification (Schröder

³Few studies directly compare the effort reduction in AL between traditional models and LLMs, but Romberg and Escher (2022) show, e.g., that LLMs can halve the manual effort.

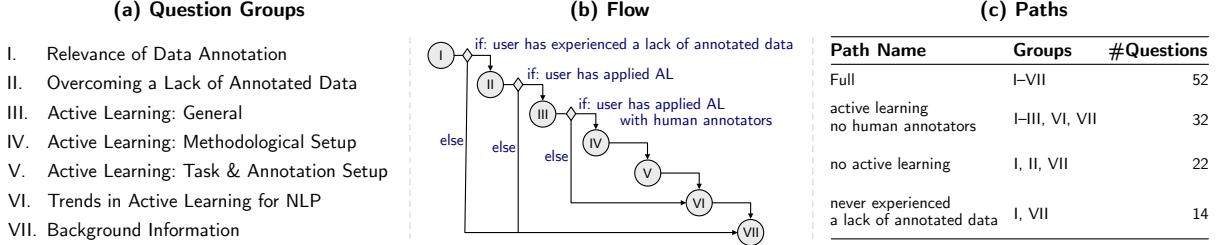


Figure 2: This diagram illustrates (a) the names and sequence of questions groups, (b) the logical flow, including branching points and conditions, and (c) possible survey paths, ordered by the number of questions.

and Niekler, 2020), or entity recognition (Kohl et al., 2024). These surveys compile academic literature, which includes both simulated experiments, and evaluations of practical applications of AL. The latter are rarer, and more importantly, represent only the small portion of practical applications that have been documented in a scientific setting. The simulated experiments, in contrast, provide only limited insights into the practical realities (Margatina and Aletras, 2023). As a consequence, important insights, such as negative results and practical obstacles, are likely missing.

Prior community surveys Literature surveys primarily focus on academic developments in the field, as they often are limited to scientific novelty. Community surveys—the collection of opinions from a specific group of people through alternative methodologies such as questionnaires—have proven to be an effective way to overcome such limitations in NLP (e.g., Zhou et al., 2022; Subramonian et al., 2023; Michael et al., 2023; Blaschke et al., 2024). In all cases, knowledge was gathered that could not be inferred from the literature alone.

For the field of AL, to the best of our knowledge, there has only one community survey been conducted as early as 2009 by Tomanek and Olsson. The authors consulted the NLP community on its experiences with AL, revealing critical issues in the practical realization. These include the effectiveness of reducing annotation costs, insufficient annotation tools, setup-related variables such as sampling complexity and waiting time between annotation cycles. As AL has evolved, *there is a need for an up-to-date community survey that captures its current state*. This paper aims to fill that gap.

3 Survey Methodology

We devise and conduct an online community survey to gain insights on topics that are rarely covered by publications. The study examines data annotation

and AL in NLP in both research and practice, focusing on its practical usage, methodologies, and remaining challenges. The five research questions that we pose in this context are:

- RQ1. Is data annotation for supervised learning still a challenge in the age of LLMs?
- RQ2. Is AL (still) useful for overcoming the data annotation bottleneck, what are alternatives?
- RQ3. What does the setup of contemporary AL look like, and what are common challenges?
- RQ4. What are notable current trends in AL and which developments are to be expected next?
- RQ5. How has AL changed over the last 15 years?

In particular, we investigate how LLMs and other recent advancements have influenced AL, and we consider the future prospects of AL, asking whether the field will experience renewed growth or contract into a niche.

3.1 Survey Design

With the aim to answer these research questions, we designed a survey encompassing 52 questions. The questions are partitioned into 7 question groups as shown in Figure 2a, which we will refer to by question group I to VII in the following.

We use branching logic (Figure 2b) to guide participants through the survey, ensuring they only see relevant questions. The main criteria here are having (i) experienced a lack of annotated data, (ii) applied AL in either setting (i.e., simulation or practical), and (iii) used AL in practical settings with human annotators. Questions are automatically skipped if participants are ineligible to answer based on prior responses. For example, participants who have never applied AL will not be shown groups III–VI that revolve around AL (see Figure 2c for the different user groups). Thereby we aim to minimize the required effort for completing the survey, which is more appreciative of the

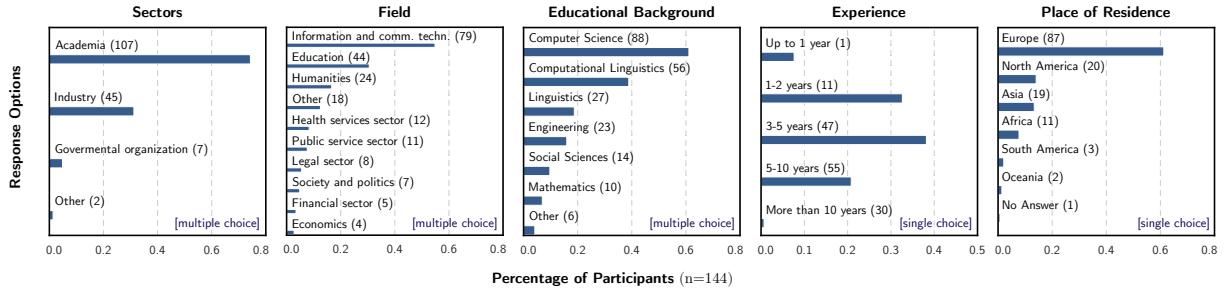


Figure 3: Exploratory histograms of the participants’ work sectors, field, educational background, work experience, and place of residence (cf. VII.1-5). The x-axis is scaled depending on the smallest and largest percentage value.

participants’ time, and also has been shown to positively affect the completion rates (Liu and Wronski, 2018). The full survey is provided in Appendix C, including information on each question’s format (i.e., free-form, multiple or single choice).

3.2 Consent, Data Usage, and Privacy

We implemented measures to ensure compliance with the EU General Data Protection Regulation. The survey was generally conducted anonymously, and participants consented to an anonymized release of their input. See Appendix B.4 for details.

3.3 Target Audience

Following Tomanek and Olsson (2009), the survey is targeted at the NLP domain. Within this community, we expect most to fall into the non-mutually exclusive categories of researcher or practitioner—both of which roles we consider relevant. The minimum eligibility to participate in the survey is basic knowledge of supervised learning for NLP.

3.4 Distribution

We distributed the survey through various channels aiming to reach a broad audience: (1) mailing lists (ACL, ELRA corpora, ELRA SIGUL, Natural Language Processing DC, tada.cool); (2) personalized email to a manually curated list of 601 individuals who co-authored papers on AL at major *CL venues between 2009 and 2024, and further 9 personal contacts; (3) common social media channels (LinkedIn, Bluesky, Twitter/X, Hugging Face Posts); (4) outreach to annotation tool developers and providers, asking them to share the survey with their users. Supplementary details on distribution and implementation are provided in Appendix B.

The survey was open online to voluntary participants for 6 weeks, from December 15th, 2024, to January 26th, 2025. Calls for participation were shared in three waves: the initial invitation at the

start of the survey period, a first reminder after two weeks, and a second reminder after four weeks.

4 Results

We first present statistics about the participants and then analyze the responses corresponding to RQ1–RQ4, deferring the discussion of RQ5 to Section 5. Table 3 in Appendix D lists the response distributions for all 52 survey questions. Throughout the remainder, we link specific arguments in the main body to related questions in this table by question group and number, e.g., I.1 for the first question.

The survey offers predefined and free-form response options. We call the latter *other* responses, and assess them through qualitative coding, involving normalization and grouping of the inputs.

4.1 Participant Statistics

Among 171 persons that navigated to the first question group, 144 completed the survey.⁴ This corresponds to a completion rate of 84% of those that entered the content part of the survey. Incomplete responses were excluded from analysis.

Figure 3 presents a demographic summary of the 144 participants. Most work in academia, but a substantial portion is employed in industry. Information and communications technology clearly leads the field of current work, while the educational background is primarily in computer science and computational linguistics. Overall, the participants are very experienced in NLP, with the majority having between 3 to 10 years of experience.

While we received responses across 6 continents, there is a bias towards Europe. This may be due to a strong representation of the European NLP community in some mailing lists, which also were the most effective referral source (51%, cf. VII.7)

⁴Compared to other community surveys (Zhan et al., 2022; Subramonian et al., 2023; Michael et al., 2023; Blaschke et al., 2024), 144 full responses place us mid-range of participation.

4.2 Annotation Bottlenecks in Times of LLMs

Our first research question is whether the annotation of sufficient amounts of training data is still a problem (RQ1). We begin by filtering participants who ever encountered difficulties due to a lack of annotated data. This applies to the vast majority: 138 out of 144 (cf. I.1). The circumstances are diverse, including working with under-resourced languages (56%), certain tasks (70%), and specific requirements (most prevalent here are domain-specificity—most free-form responses also hint at that—and working with many, at times greatly under-represented, classes) (51%) (cf. I.2).

Following this initial stocktaking, we are interested in potential changes in difficulties given recent advancements in NLP. Figure 4 illustrates the attitude on five questions about the relevance of data annotation currently. Overall, participants largely agree that many problems will still require supervised learning (80%). Annotated data remains a limiting factor here; in general (94%), for certain languages (75%), and for problems of a certain complexity (91%). Moreover, for their tasks, only few participants agree that generative AI for training data synthesis offers a viable solution (30%).

Answer to RQ1: Supervised learning remains important in the age of LLMs. Data annotation is still a bottleneck, especially in demanding scenarios.

4.3 Overcoming Annotation Bottlenecks

We next examine the use of computational methods for data-efficient annotation, asking if AL is still considered useful and exploring alternatives (RQ2). Of the 138 respondents who faced challenges due to a lack of annotated data, 120 had used computational methods to address this issue (cf. II.1). See Figure 5a for an overview of the methods (cf. II.2).

Usage of active learning Notably, AL had been used by over half of the respondents. The primary motivation for choosing AL was to obtain annotated data at minimal cost (87%), gaining practical experience (46%) and identifying difficult examples in annotation guidelines (24%). Other options (8%) added the improvement of data quality and AL for research purposes (cf. III.2).

When asking why participants had not chosen AL, 25% had never heard of it, and 50% cited insufficient expertise. There were also methodological concerns, such as the expected implementation overhead and the lack of (or unawareness about) suitable annotation tools (47%). Additionally, 14%

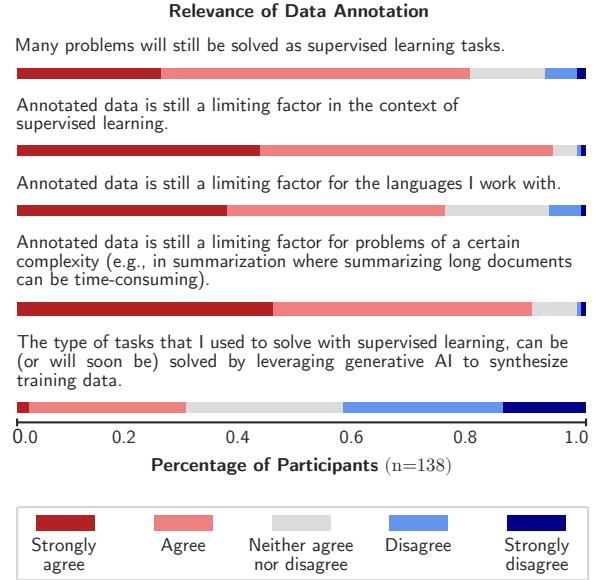


Figure 4: Respondents’ assessment of the relevance of data annotation in context of recent advancements in NLP using a 5-point Likert scale (cf. I.3–7).

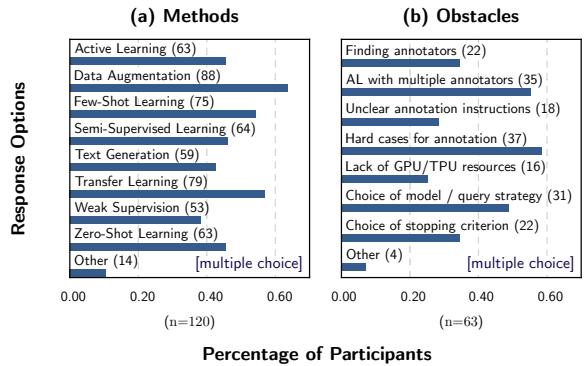


Figure 5: Participants’ general experience with computational methods for a lack of annotated data (a) and obstacles especially faced in the application of AL (b).

doubted AL’s effectiveness at all, 12% hesitated due to the difficulty of estimating effectiveness upfront, 18% pointed to sampling bias, and 9% found it unsuitable due to specific project requirements. Other reasons include non-aligning goals, such as studying specific phenomena, and a complete lack of annotation budget (cf. II.5). Despite these concerns, 54% of participants who had not yet used AL consider its application in future projects and further 38% indicated they are merely uncertain due to a lack of knowledge. Only one participant answered no (reasoning that AL does not work well enough in practice; cf. II.8), while four made its use dependent on the specific circumstances (cf. II.7).

The current users of AL also report obstacles in data annotation with AL, illustrated in Figure 5b,

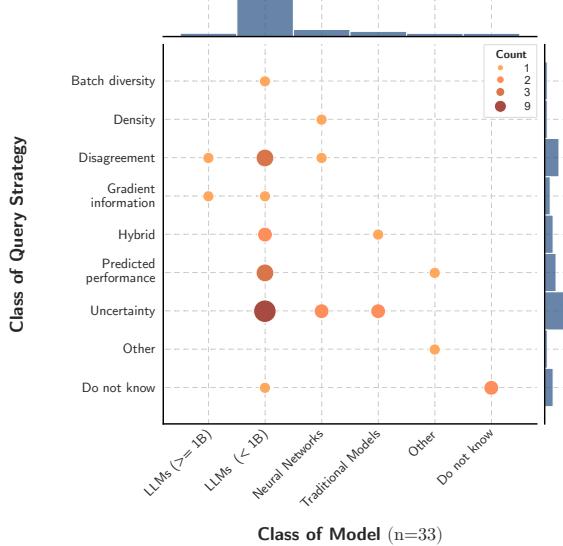


Figure 6: Distribution of the reported models and query strategies. Marginal distributions are shown on the side.

which may lead them to opt for alternatives instead. The most pronounced challenge is handling hard annotation cases, followed by the involvement of multiple annotators. The third major hurdle is selecting an appropriate model and query strategy. In the other responses, the need for open, robust, and user-friendly AL tools was emphasized (cf. III.3).

Alternative methods Computational alternatives to AL are widely dispersed across participants (see Figure 5a), but we observe that only data augmentation, transfer learning, and few-shot learning have been used more frequently than AL. In general, the alternative methods were considered successful in overcoming a lack of annotated data in slightly over half of the cases (57%, cf. II.4). In comparison, recent AL-based annotation projects were considered successful in 91% and effective in 67% of cases (see Section 4.4 for more details).

Answer to RQ2: The strong openness to using AL suggests it is considered a useful method for data annotation despite available alternatives.

4.4 Contemporary Active Learning

We further examine AL by inquiring what it, especially in the context of LLMs, looks like nowadays (RQ3). This section focuses on the 33 reported applied AL projects with human annotators (out of 48) that were conducted recently, starting within the last five years (2020 onward; cf. III.5, IV.1).

Models, query strategies, and stopping criteria

Figure 6 provides an overview of models and query

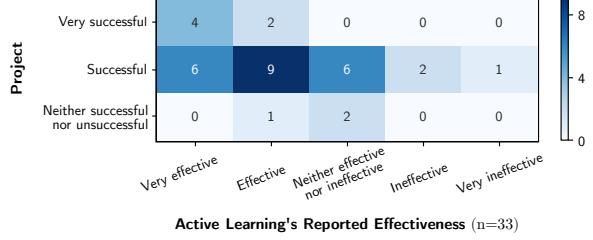


Figure 7: The reported project success broken down by effectiveness of AL. Unselected options for project success are omitted (unsuccessful, very unsuccessful).

strategies used. The majority of projects relied on LLMs, with a clear preference for smaller models such as BERT. Notably, only two recent projects employed larger language models (in the context of our survey with 1B parameters and above). Uncertainty sampling emerged as the dominant query strategy, despite the wide range of alternatives. Among the other options, we observe the tryout of multiple models and query strategies, as well as AutoML libraries for model selection (cf. IV.2,3). For stopping the AL process, most projects halted upon budget depletion (39%), after evaluation of the model on a held-out gold standard (30%) or via human assessment (one other response). Fixed numbers of documents, iterations or instances are less common (4 occurrences, the latter two noted in other). Algorithmic stopping criteria are still rare, used in only 12% of cases (cf. IV.5).

We also inquired regarding encountered waiting times and the maximum acceptable waiting times. Contrary to our expectations, participants are willing to wait considerable times up to one week; over 50% even as long as one day (cf. IV.4, III.4).

Annotation tools for active learning Given the availability of annotation tools with AL support, we asked participants about their usage. Interestingly, just over half of the projects used an annotation tool with AL support (17). These include Argilla (4), LabelSleuth (3), Prodigy (2), ActiveAnno (1), ALAMBIC (1), ALANNO (1), and Label Studio (1). 4 projects used self-built solutions (cf. V.6,7).

Satisfaction with project Figure 7 illustrates the perceived success of the annotation projects together with the perceived effectiveness of using AL. Overall, most projects were considered successful with an effective AL contribution. At the same time, especially for successful projects, it can be observed that the perception of AL effectiveness ranges from very high to very low (cf. V.11, V.12).

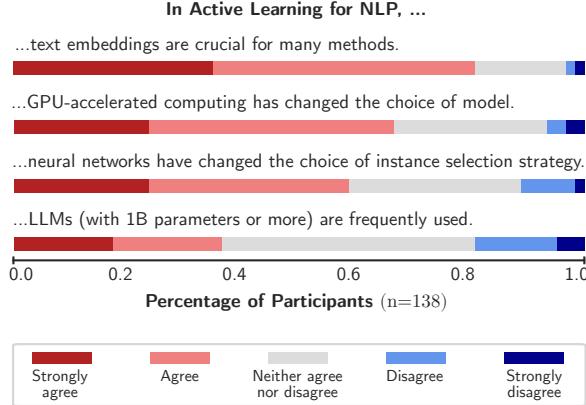


Figure 8: Participants’ assessment of the impact of various methodological and technological developments on AL using a 5-point Likert scale (cf. VI.1–4).

Among those that reported a reduced effectiveness, the main reasons were the lack of suitable annotation tools (24%; notably, 4 had used a tool with AL support) and the overhead of setup (21%), which connects to insufficient knowledge in retrospect (17%). Performance mismatches contributed, such as poor overall performance (21%), a lack of effort reduction (9%), inaccurate efficiency estimation (9%), and mismatching project-specific requirements (6%). In addition, respondents noted sampling bias (15%) and dataset-model dependency (15%). Other options stress concerns about setup time and effectiveness (cf. V.13). We observe a similar trend across sectors, in both academia and industry (details in Appendix D.3).

Overall, 42 out of 48 AL practitioners stated they would use AL again in future projects. Two respondents restricted its use to specific scenarios, while another two remained uncertain. Only two respondents would not use AL again, noting that AL does not work well enough in practice (cf. V.14,15).

Answer to RQ3: Recent AL combines smaller LLMs with uncertainty sampling. Main challenges are the setup complexity (overhead, efficiency estimates, knowledge), general project risks (performance, effort reduction, sampling bias, model dependency, requirements), and unsuitable tools.

4.5 Adoption of Recent Trends and Next Steps

We now turn to recent and then future trends in AL (RQ4). Figure 8 illustrates the perceived impact of four important developments for NLP over the last decade. Among these, participants particularly emphasized the importance of text embeddings, GPU-accelerated computing, and neural networks.

LEVERAGING LANGUAGE MODELS	
1.	(Partially) using LLMs as annotators (8)
2.	Increased use of LLMs in AL components (7)
3.	Data synthesis during or before AL (4)
4.	Incorporate language model-based agents (3)
5.	Improved usage of embeddings (2)
6.	Using small efficient models (2)
ADVANCEMENTS IN ACTIVE LEARNING	
1.	More sophisticated query strategies (4)
2.	Effectiveness over random sampling (2)
3.	More reliable, well-calibrated uncertainty scores (2)
TOOLING	
1.	Improvements in convenience (4)
2.	Easier bootstrapping of an AL setup (2)
OTHER	
1.	AL for low-resource languages (2)
2.	AL for subjective tasks (1)

Table 1: Participant-identified trends in AL for NLP.

In contrast, the use of parameter-heavy LLMs was more controversial. This aligns with the findings from applied AL projects (see Section 4.4).

We furthermore asked participants in a free-form question about next trends for AL in NLP that they expect to impact the field. Table 1 shows the results of our qualitative analysis. As expected, the majority of anticipated developments focus on the integration of LLMs at various stages. With regard to the components of AL, the development of effective and more sophisticated query strategies is expected. There is also a call for more reliable, well-calibrated uncertainty scores. Further responses hint at advancements in tooling or improvements for low-resource languages and subjective tasks. There is initial research approaching these trends (e.g., Xiao et al. 2023; Kholodna et al. 2024; Liang et al. 2024; Hassan et al. 2025).

Answer to RQ4: GPU-accelerated language modeling plays a key role now and in future AL. Most trends center on integrating (small) LLMs—into components, for data synthesis, or as agents.

5 Discussion

The results captured valuable insights, but what are the broader implications for the field of AL?

Active learning remains relevant Linking back to the title question of this survey, our findings suggest that AL has not become obsolete in light of LLMs and related developments. Instead, AL is frequently used and perceived as an effective solution for the still critical factor of annotated data in supervised learning, despite popular alterna-

tives. Moreover, combining AL with some of these methods such as few-shot learning or data synthesis shows potential for improving efficiency (e.g., Gonsior et al., 2020; Bayer and Reuter, 2024).

As LLMs improve, annotation needs may shift toward few-shot learning for simpler tasks. However, AL will still be important especially in context of more complex tasks, as well as secondary applications such as the (continued) refinement of annotation guidelines (Schröder and Heyer, 2024), detecting annotation errors (Weber and Plank, 2023), and handling human label variation (Wang and Plank, 2023; Van Der Meer et al., 2024).

Has active learning outgrown earlier problems?

Using the 2009 survey as reference, we examine how the perception of AL has changed (RQ5). Since the available data collection methodology does not allow us to claim representativeness of the NLP community for the two distinct samples, we focus on comparing central findings rather than conducting longitudinal statistical analyses.

We first note a growing adoption of AL, indicated by the share of respondents reporting its use increasing from 20% in 2009 to 50% in this study.⁵ AL also appears to expand more and more beyond academical application towards industry practitioners. The setup of AL has naturally shifted towards LLMs as the model of choice. At the same time, uncertainty sampling remains the preferred query strategy, despite the growing range of alternatives. Although setting up AL for practical use remains a challenge, deciding when to stop does not appear to be; information-theoretical grounds for halting the annotation process are still oftentimes trumped by practical constraints such as time and budget.

Crucially, central challenges first reported by Tomanek and Olsson (2009) remain unsolved, as echoed by the current survey. The complexities of setting up an AL-based annotation workflow, coupled with the uncertainty of its cost-effectiveness and perceived poor support in annotation tools, make this an area primarily accessible for experts, while also the goalposts may have shifted considering especially the dissatisfaction with tooling despite ongoing product development in this area.

Answer to RQ5: Adoption of AL has increased and AL has been substantially influenced by LLMs. Contemporary key issues (RQ3) persist since 2009.

⁵While the 2009 survey used only mailing lists, we added direct invitations to AL researchers. This may introduce some bias, although most invitees were also on the mailing lists.

Practical barriers and a call to action To strengthen AL in the long term, the three key issues need to be addressed: (1) *Excessive complexity of the AL setup*: Respondents who never had applied AL most commonly mentioned a lack of methodological expertise and implementation overhead as obstructing factors. AL users partly share the concerns regarding methodological choices. (2) *Risk of starting an AL project*: Respondents noted that the cost reduction through AL cannot be reliably estimated upfront. Its dependence on numerous variables makes a priori chosen setups prone to unsatisfactory outcomes, possibly worse than random sampling (Ghose and Nguyen, 2024). (3) *Perceived insufficiency of tooling*, despite considerable developments in this area since the earlier survey.

We call for future efforts to (1) instead of developing new algorithms prioritize the reduction of existing complexity (e.g., by revisiting previous strategies and refuting their effectiveness through theoretical or empirical investigation); (2) providing guidance for choosing AL components based on task variables, such as data characteristics, increasing the probability for a successful AL setup (e.g., by developing heuristics); (3) enhancing the visibility of existing tools; using the participants' feedback to further improve tooling, e.g., by building interfaces that are tailored to guiding non-experts (Ras et al., 2022) through the adaption of AL (Shnarch et al., 2022b; Jukić et al., 2023).

6 Conclusions

To gain comprehensive insights into AL in the era of LLMs, we conducted an online survey in the NLP community. Through five research questions we reassess the relevance of data annotation, investigate the relevance and contemporary problems of AL, and try to anticipate the next trends in AL. While participants report that recent advancements have only partly permeated to AL yet, and the use of LLMs in AL is still on the rise, they are overall positive on the suitability of LLMs for AL. Our analysis reveals that three longstanding problems are still relevant: participants consider the AL workflow as difficult to implement, struggle with uncertainty of its cost-effectiveness, and express a continued need for improved tooling. We propose directions to alleviate each of these problems, aiming to refocus future AL research onto core issues in the field—thereby enhancing its impact and renewing attention to its practical relevance.

Limitations

Representativeness of the community survey Our results are descriptive for a sub-sample of the NLP community only, and therefore we cannot draw conclusions for the entirety of the community. As shown in Figure 3, our distribution strategy led to a potential over-representation of academia as a work sector and European countries (primarily Germany). While the geographic reach is broad (covering 44 countries in total), a stronger representation from North America and Asia was expected.⁶ Moreover, as our survey is distributed in English, this may introduce a language bias, possibly excluding respondents who are not proficient in English or decide against responding due to being uncomfortable responding in English. However, distributing the survey in multiple languages seems infeasible given the vast number of written languages.

Temporal bias in perception It is difficult to determine when participants formed their opinions on AL, as assessments are commonly based on past experiences that may not align with current advancements. Similarly, we cannot ensure that recent improvements in AL were acknowledged or influenced their opinion. As a result, the collected responses may have a certain temporal bias, potentially pointing to issues that have since been improved upon or even resolved. However, our analysis of recent projects confirms that the three key challenges (setup complexity, cost reduction estimation, and tooling) persist, to a certain extent.

Constraints of active learning in low-resource language scenarios Naturally, AL can be suitable in scenarios in which *annotated resources are scarce*, and yet *non-annotated data is available*. However, limitations apply where using machine learning-based methods to tackle NLP tasks may be prevented by the almost complete lack of language-specific data (be it annotated or non-annotated) as well as non-existing NLP pipelines and tools. As some of our survey participants pointed out in the free-form text fields, non-machine learning techniques often have to be applied for those languages, and in consequence, AL cannot provide a solution here. We recognize that especially in the low-resource language field non-machine learning based approaches are still relevant today.

⁶<http://stats.aclrollingreview.org/submissions/geodiversity/>, <https://www.marekrei.com/blog/geographic-diversity-of-nlp-conferences/>

Ethical Considerations

To comply with data protection laws, we took the necessary steps to ensure compliance with the EU General Data Protection Regulation. Respondents granted their consent to the storage and analysis of their provided data, and the distribution of an anonymized version thereof, before starting the survey. To allow the NLP community for extended analysis of the collected information and to uphold scientific transparency, we will publish the resulting dataset in a form that does not allow to infer conclusions about individuals.

Given the growing skepticism about data usage, particularly in the context of generative AI, and the voluntary nature of survey participation, we opted for a non-commercial license (i.e., CC BY-NC-SA 4.0⁷). This approach ensures that the data can be accessed and used for research purposes while safeguarding respondents' privacy and addressing concerns about potential misuse.

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⁷<https://creativecommons.org/licenses/by-nc-sa/4.0/>

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References

- Markus Bayer and Christian Reuter. 2024. [Activellm: Large language model-based active learning for textual few-shot scenarios](#). *Preprint*, arXiv:2405.10808.
- Verena Blaschke, Christoph Purschke, Hinrich Schuetze, and Barbara Plank. 2024. [What do dialect speakers want? a survey of attitudes towards language technology for German dialects](#). In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 823–841, Bangkok, Thailand. Association for Computational Linguistics.
- Ekaterina Borisova, Raia Abu Ahmad, Leyla Garcia-Castro, Ricardo Usbeck, and Georg Rehm. 2024. [Surveying the FAIRness of annotation tools: Difficult to find, difficult to reuse](#). In *Proceedings of The 18th Linguistic Annotation Workshop (LAW-XVIII)*, pages 29–45, St. Julians, Malta. Association for Computational Linguistics.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, and 12 others. 2020. [Language models are few-shot learners](#). In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.
- Liat Ein-Dor, Alon Halfon, Ariel Gera, Eyal Shnarch, Lena Dankin, Leshem Choshen, Marina Danilevsky, Ranit Aharonov, Yoav Katz, and Noam Slonim. 2020. [Active Learning for BERT: An Empirical Study](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7949–7962, Online. Association for Computational Linguistics.
- Yifan Fu, Xingquan Zhu, and Bin Li. 2013. [A survey on instance selection for active learning](#). *Knowledge and Information Systems*, 35(2):249–283.
- Daria Galimzianova and Leonid Sanochkin. 2024. [Efficient active learning with adapters](#). In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 14374–14383, Miami, Florida, USA. Association for Computational Linguistics.
- Abhishek Ghose and Emma Thuong Nguyen. 2024. [On the fragility of active learners for text classification](#). In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 22217–22233, Miami, Florida, USA. Association for Computational Linguistics.
- Fabrizio Gilardi, Meysam Alizadeh, and Maël Kubli. 2023. [Chatgpt outperforms crowd workers for text-annotation tasks](#). *Proceedings of the National Academy of Sciences*, 120(30):e2305016120.
- Julius Gonsior, Maik Thiele, and Wolfgang Lehner. 2020. [Weakal: Combining active learning and weak supervision](#). In *Discovery Science*, pages 34–49, Cham. Springer International Publishing.
- Sabit Hassan, Anthony B. Sicilia, and Malihe Alikhani. 2025. [An active learning framework for inclusive generation by large language models](#). In *Proceedings of the 31st International Conference on Computational Linguistics*, pages 5403–5414, Abu Dhabi, UAE. Association for Computational Linguistics.
- Yufang Hou, Charles Jochim, Martin Gleize, Francesca Bonin, and Debasis Ganguly. 2021. [TDMSci: A specialized corpus for scientific literature entity tagging of tasks datasets and metrics](#). In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 707–714, Online. Association for Computational Linguistics.
- Josip Jukić, Fran Jelenić, Miroslav Bičanić, and Jan Snajder. 2023. [ALANNO: An active learning annotation system for mortals](#). In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations*, pages 228–235, Dubrovnik, Croatia. Association for Computational Linguistics.
- Natalia Kholodna, Sahib Julka, Mohammad Khodadadi, Muhammed Nurullah Gumus, and Michael Granitzer. 2024. [LLMs in the loop: Leveraging large language model annotations for active learning in low-resource languages](#). In *Machine Learning and Knowledge Discovery in Databases. Applied Data Science Track: European Conference, ECML PKDD 2024, Vilnius, Lithuania, September 9–13, 2024, Proceedings, Part X*, page 397–412, Berlin, Heidelberg. Springer-Verlag.
- Jan-Christoph Klie, Michael Bugert, Beto Boulosa, Richard Eckart de Castilho, and Iryna Gurevych. 2018. [The INCEPTION platform: Machine-assisted and knowledge-oriented interactive annotation](#). In

- Proceedings of the 27th International Conference on Computational Linguistics: System Demonstrations*, pages 5–9, Santa Fe, New Mexico. Association for Computational Linguistics.
- Philipp Kohl, Yoka Krämer, Claudia Fohry, and Bodo Kraft. 2024. Scoping review of active learning strategies and their evaluation environments for entity recognition tasks. In *Deep Learning Theory and Applications*, pages 84–106, Cham. Springer Nature Switzerland.
- Dongseop Kwon, Sun Kim, Soo Yong Shin, and John Wilbur. 2013. Bioqrator: a web-based interactive biomedical literature curating system. In *Proceedings of the fourth biocreative challenge evaluation workshop*, volume 1, pages 241–246.
- Florian Laws and Hinrich Schütze. 2008. Stopping criteria for active learning of named entity recognition. In *Proceedings of the 22nd International Conference on Computational Linguistics (Coling 2008)*, pages 465–472, Manchester, UK. Coling 2008 Organizing Committee.
- David D. Lewis and William A. Gale. 1994. A sequential algorithm for training text classifiers. In *Proceedings of the 17th Annual International ACM-SIGIR Conference on Research and Development in Information Retrieval*, pages 3–12. Springer, ACM/Springer.
- Dongyuan Li, Ying Zhang, Zhen Wang, Shiyin Tan, Satoshi Kosugi, and Manabu Okumura. 2024. Active learning for abstractive text summarization via LLM-determined curriculum and certainty gain maximization. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 8959–8971, Miami, Florida, USA. Association for Computational Linguistics.
- Jinggui Liang, Lizi Liao, Hao Fei, Bobo Li, and Jing Jiang. 2024. Actively learn from LLMs with uncertainty propagation for generalized category discovery. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 7845–7858, Mexico City, Mexico. Association for Computational Linguistics.
- Mingnan Liu and Laura Wronski. 2018. Examining completion rates in web surveys via over 25,000 real-world surveys. *Social Science Computer Review*, 36(1):116–124.
- Haocheng Luo, Wei Tan, Ngoc Nguyen, and Lan Du. 2023. Re-weighting tokens: A simple and effective active learning strategy for named entity recognition. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 12725–12734, Singapore. Association for Computational Linguistics.
- Katerina Margatina and Nikolaos Aletras. 2023. On the limitations of simulating active learning. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 4402–4419, Toronto, Canada. Association for Computational Linguistics.
- Katerina Margatina, Timo Schick, Nikolaos Aletras, and Jane Dwivedi-Yu. 2023. Active learning principles for in-context learning with large language models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 5011–5034, Singapore. Association for Computational Linguistics.
- Katerina Margatina, Giorgos Vernikos, Loïc Barrault, and Nikolaos Aletras. 2021. Active learning by acquiring contrastive examples. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 650–663, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Vânia Mendonça, Ricardo Rei, Luísa Coheur, and Alberto Sardinha. 2023. Onception: Active learning with expert advice for real world machine translation. *Computational Linguistics*, 49(2):325–372.
- Julian Michael, Ari Holtzman, Alicia Parrish, Aaron Mueller, Alex Wang, Angelica Chen, Divyam Madaan, Nikita Nangia, Richard Yuanzhe Pang, Jason Phang, and Samuel R. Bowman. 2023. What do NLP researchers believe? results of the NLP community metasurvey. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 16334–16368, Toronto, Canada. Association for Computational Linguistics.
- Charlotte Nachtegael, Jacopo De Stefani, and Tom Lenaerts. 2023a. ALAMBIC : Active learning automation methods to battle inefficient curation. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations*, pages 117–127, Dubrovnik, Croatia. Association for Computational Linguistics.
- Charlotte Nachtegael, Jacopo De Stefani, and Tom Lenaerts. 2023b. A study of deep active learning methods to reduce labelling efforts in biomedical relation extraction. *PLOS ONE*, 18(12):1–23.
- Fredrik Olsson. 2009. A literature survey of active machine learning in the context of natural language processing. SICS Technical Report T2009:06, Swedish Institute of Computer Science.
- Fredrik Olsson and Katrin Tomanek. 2009. An intrinsic stopping criterion for committee-based active learning. In *Proceedings of the Thirteenth Conference on Computational Natural Language Learning (CoNLL-2009)*, pages 138–146, Boulder, Colorado. Association for Computational Linguistics.
- Jixin Pei, Aparna Ananthasubramaniam, Xingyao Wang, Naitian Zhou, Apostolos Dedeloudis, Jackson Sargent, and David Jurgens. 2022. POTATO: The portable text annotation tool. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*,

- pages 327–337, Abu Dhabi, UAE. Association for Computational Linguistics.
- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.
- Gabrielle Ras, Ning Xie, Marcel van Gerven, and Derek Doran. 2022. *Explainable deep learning: A field guide for the uninitiated*. *J. Artif. Int. Res.*, 73.
- Anna Rogers and Sasha Luccioni. 2024. Position: Key claims in LLM research have a long tail of footnotes. In *Forty-first International Conference on Machine Learning*.
- Julia Romberg and Tobias Escher. 2022. Automated topic categorisation of citizens’ contributions: Reducing manual labelling efforts through active learning. In *Electronic Government*, pages 369–385, Cham. Springer International Publishing.
- Christopher Schröder and Gerhard Heyer. 2024. Self-training for sample-efficient active learning for text classification with pre-trained language models. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 11987–12004, Miami, Florida, USA. Association for Computational Linguistics.
- Christopher Schröder and Andreas Niekler. 2020. A survey of active learning for text classification using deep neural networks. *Preprint*, arXiv:2008.07267.
- Burr Settles. 2009. Active learning literature survey. Computer Sciences Technical Report 1648, University of Wisconsin–Madison.
- Artem Shelmanov, Vadim Liventsev, Danil Kireev, Nikita Khromov, Alexander Panchenko, Irina Fedulova, and Dmitry V. Dylov. 2019. Active learning with deep pre-trained models for sequence tagging of clinical and biomedical texts. In *2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pages 482–489.
- Artem Shelmanov, Dmitri Puzyrev, Lyubov Kupriyanova, Denis Belyakov, Daniil Larionov, Nikita Khromov, Olga Kozlova, Ekaterina Artemova, Dmitry V. Dylov, and Alexander Panchenko. 2021. Active learning for sequence tagging with deep pre-trained models and Bayesian uncertainty estimates. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1698–1712, Online. Association for Computational Linguistics.
- Eyal Shnarch, Alon Halfon, Ariel Gera, Marina Danilevsky, Yannis Katsis, Leshem Choshen, Martin Santillan Cooper, Dina Epelboim, Zheng Zhang, and Dakuo Wang. 2022a. Label sleuth: From unlabeled text to a classifier in a few hours. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 159–168, Abu Dhabi, UAE. Association for Computational Linguistics.
- Eyal Shnarch, Alon Halfon, Ariel Gera, Marina Danilevsky, Yannis Katsis, Leshem Choshen, Martin Santillan Cooper, Dina Epelboim, Zheng Zhang, Dakuo Wang, Lucy Yip, Liat Ein-Dor, Lena Dankin, Ilya Shnayderman, Ranit Aharonov, Yunyao Li, Nafatali Liberman, Philip Levin Slesarev, Gwilym Newton, and 3 others. 2022b. Label sleuth: From unlabeled text to a classifier in a few hours. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 159–168, Abu Dhabi, UAE. Association for Computational Linguistics.
- Arjun Subramonian, Xingdi Yuan, Hal Daumé III, and Su Lin Blodgett. 2023. It takes two to tango: Navigating conceptualizations of NLP tasks and measurements of performance. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 3234–3279, Toronto, Canada. Association for Computational Linguistics.
- Katrin Tomanek and Fredrik Olsson. 2009. A web survey on the use of active learning to support annotation of text data. In *Proceedings of the NAACL HLT 2009 Workshop on Active Learning for Natural Language Processing*, pages 45–48, Boulder, Colorado. Association for Computational Linguistics.
- Manuel Tonneau, Dhaval Adjodah, Joao Palotti, Nir Grinberg, and Samuel Fraiberger. 2022. Multilingual detection of personal employment status on Twitter. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6564–6587, Dublin, Ireland. Association for Computational Linguistics.
- Akim Tsvigun, Ivan Lysenko, Danila Sedashov, Ivan Lazichny, Eldar Damirov, Vladimir Karlov, Artemy Belousov, Leonid Sanochkin, Maxim Panov, Alexander Panchenko, Mikhail Burtsev, and Artem Shelmanov. 2022a. Active learning for abstractive text summarization. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 5128–5152, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Akim Tsvigun, Leonid Sanochkin, Daniil Larionov, Gleb Kuzmin, Artem Vazhentsev, Ivan Lazichny, Nikita Khromov, Danil Kireev, Aleksandr Rubashevskii, Olga Shahmatova, Dmitry V. Dylov, Igor Galitskiy, and Artem Shelmanov. 2022b. ALToolbox: A set of tools for active learning annotation of natural language texts. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 406–434, Abu Dhabi, UAE. Association for Computational Linguistics.
- Michiel Van Der Meer, Neele Falk, Pradeep K. Mrukannaiah, and Enrico Liscio. 2024. Annotator-centric active learning for subjective NLP tasks. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 18537–18555, Miami, Florida, USA. Association for Computational Linguistics.

- Andreas Vlachos. 2008. A stopping criterion for active learning. *Computer Speech & Language*, 22(3):295–312.
- Xinpeng Wang and Barbara Plank. 2023. **ACTOR: Active learning with annotator-specific classification heads to embrace human label variation**. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 2046–2052, Singapore. Association for Computational Linguistics.
- Leon Weber and Barbara Plank. 2023. **ActiveAED: A human in the loop improves annotation error detection**. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 8834–8845, Toronto, Canada. Association for Computational Linguistics.
- Max Wiechmann, Seid Muhie Yimam, and Chris Biemann. 2021. **ActiveAnno: General-purpose document-level annotation tool with active learning integration**. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Demonstrations*, pages 99–105, Online. Association for Computational Linguistics.
- Yu Xia, Xu Liu, Tong Yu, Sungchul Kim, Ryan Rossi, Anup Rao, Tung Mai, and Shuai Li. 2024. **Hallucination diversity-aware active learning for text summarization**. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 8665–8677, Mexico City, Mexico. Association for Computational Linguistics.
- Ruixuan Xiao, Yiwen Dong, Junbo Zhao, Runze Wu, Minmin Lin, Gang Chen, and Haobo Wang. 2023. **FreeAL: Towards human-free active learning in the era of large language models**. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 14520–14535, Singapore. Association for Computational Linguistics.
- Michelle Yuan, Hsuan-Tien Lin, and Jordan Boyd-Graber. 2020. **Cold-start active learning through self-supervised language modeling**. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7935–7948, Online. Association for Computational Linguistics.
- Kamer Yüksel, Ahmet Gunduz, Mohamed Albadrashiny, and Hassan Sawaf. 2023. **EvolveMT: an ensemble MT engine improving itself with usage only**. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 5: Industry Track)*, pages 341–346, Toronto, Canada. Association for Computational Linguistics.
- Kamer Ali Yuksel, Ahmet Gunduz, Shreyas Sharma, and Hassan Sawaf. 2022. **Efficient machine translation corpus generation**. In *Proceedings of the 15th biennial conference of the Association for Machine Translation in the Americas (Workshop 2: Corpus Generation and Corpus Augmentation for Machine Translation)*, pages 11–17. Association for Machine Translation in the Americas.
- Xiangkai Zeng, Sarthak Garg, Rajen Chatterjee, Udyakumar Nallasamy, and Matthias Paulik. 2019. **Empirical evaluation of active learning techniques for neural MT**. In *Proceedings of the 2nd Workshop on Deep Learning Approaches for Low-Resource NLP (DeepLo 2019)*, pages 84–93, Hong Kong, China. Association for Computational Linguistics.
- Xueying Zhan, Qingzhong Wang, Kuan hao Huang, Haoyi Xiong, Dejing Dou, and Antoni B. Chan. 2022. **A comparative survey of deep active learning**. *Preprint*, arXiv:2203.13450.
- Ruoyu Zhang, Yanzeng Li, Yongliang Ma, Ming Zhou, and Lei Zou. 2023. **LLMaAA: Making large language models as active annotators**. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 13088–13103, Singapore. Association for Computational Linguistics.
- Zhisong Zhang, Emma Strubell, and Eduard Hovy. 2022. **A survey of active learning for natural language processing**. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 6166–6190, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Yuekai Zhao, Haoran Zhang, Shuchang Zhou, and Zhihua Zhang. 2020. **Active learning approaches to enhancing neural machine translation**. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1796–1806, Online. Association for Computational Linguistics.
- Kaitlyn Zhou, Su Lin Blodgett, Adam Trischler, Hal Daumé III, Kaheer Suleman, and Alexandra Olteanu. 2022. **Deconstructing NLG evaluation: Evaluation practices, assumptions, and their implications**. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 314–324, Seattle, United States. Association for Computational Linguistics.

Appendix

A Identification of Active Learning Publications for Figure 1

We start from the full ACL anthology as BibTeX, including abstracts (first version in the beginning of December, updated on January 31st, 2025). In a first step, only those publications were kept that have been published in the context of ACL, COLING, EACL, EMNLP, NAACL, CL, and TACL between 2009 and 2024. This includes affiliated workshops that were kept based on a hand-curated list. The resulting number of

papers constitutes the *total number of publications*. Subsequently, we filter all publications that contain “active” in their title or abstract. If “active” is directly followed by “learning”, the publication is kept without further checks, in case of other next words, we manually checked the publications for their relevance⁸. The resulting number of papers constitutes the *total number of AL publications*.

B Survey Implementation

B.1 Survey Distribution and Advertisement

We chose a diverse distribution strategy, covering mailing lists, direct contacts, social media, and service providers. While some overlap between these channels may exist, we utilize all of them to ensure a wide outreach. Our research interest is on applications for text data, thus, we advertise the survey with a focus on the NLP community.

Mailing lists We sent the call for participation via a number of mailing lists that are received by researchers and practitioners: The **ACL mailing list** covers all current members of the Association of Computational Linguistics – about 10,400 as of end of 2024. *The worldwide recipients are researchers from academia and industry likewise.*⁹ The **ELRA corpora-list** is a mailing list managed by the European Language Resources Association. It serves as a platform for sharing information related to linguistic resources, therefore *providing a way to reach researchers and practitioners involved in data annotation in their daily work*. The exact number of recipients on the mailing list is not publicly available; however, it is widely assumed as reaching a substantial audience. The members of the **ELRA SIGUL-list** are professionals involved in the development of language resources and technologies for under-resourced languages. By utilizing this mailing list, we aim to *gain a more diverse perspective on supervised learning and AL for lesser-studied languages*, trying to mitigate potential biases in data collection driven by the uneven availability of language resources. The exact number of recipients on the mailing list is not publicly available. The **Natural Language Pro-**

⁸This way, we account for wording variations such as “active fine-tuning” or “active sampling.”

⁹The call to the ACL mailing list was sent out only once, due to two reasons: first, a manual inspection period of about two weeks by the administrators before distribution limited us to requesting only two mailings during the survey period; second, our second request was deleted for unclear reasons.

cessing Data Community is a google group¹⁰ for anyone interested in NLP including computational linguists, data scientists, and software engineers. It counts 341 members as of the end of 2024. The **tada.cool initiative**¹¹ is a community of interdisciplinary researchers, with a focus on machine learning and NLP for social science applications. We reached 748 members (status at the end of 2024) via the slack channel. We also requested distribution via the linguistlist¹², but did not receive approval.

Social media To gather more technical and applied perspectives, we identified several chat communities focused on NLP and machine learning topics (e.g., PyTorch Lightning, Hugging Face Discord, and Hugging Face Posts) and sought approval to share the survey on these platforms. Approval was granted for the latter two, and the call for participation was subsequently posted. Moreover, we posted participation requests on several social media platforms (LinkedIn, X, and Bluesky), which are frequented by both audiences. These posts were also re-shared by non-author accounts, further extending the survey’s reach.

Researchers working on AL in NLP We curated a list of researchers who have co-authored one or more publications in major NLP venues over the past 15 years with AL as the central topic. To compile this list of experts, we started from the AL publications identified as described in Appendix A. We manually extracted the email addresses from all publications that mentioned AL directly in the title. The approach also includes papers from workshops co-located with conferences to capture more researchers that have worked on practical application use cases. We contacted all 601 identified individuals by a personalized mail. In 139 cases, the e-mail addresses extracted from the papers were no longer functional. We added 9 existing personal contacts to complement the list of active researchers. These were likewise contacted per mail.

Annotation tool providers As an additional strategy to incorporate practical insights from individuals involved in dataset creation efforts—potentially supported by AL—we reached out to individuals and companies responsible for annotation tools with AL solutions for text annotation.

To identify relevant tools, we relied on a recent

¹⁰<https://groups.google.com/a/datacommunitydc.org/g/nlp>

¹¹<https://sites.google.com/view/polsci-ml-initiative/talks>

¹²<https://linguistlist.org/submit/qs/>

survey of annotation tools (Borisova et al., 2024) and supplemented this with additional tools that we have encountered through years of research in the field. The resulting list of contacted tools is: ActiveAnno (Wiechmann et al., 2021), AL Toolbox (Tsvigun et al., 2022b), Argilla¹³, AWS Sagemaker Ground Truth and Comprehend, Bio-QRator (Kwon et al., 2013), CleanLab¹⁴, INCEPTION (Klie et al., 2018), Labelbox¹⁵, Label Sleuth (Shnarch et al., 2022a), Label Studio¹⁶, MITRE Annotation Toolkit (MAT)¹⁷, and POTATO (Pei et al., 2022). We also contacted several companies and services via their official communication channels (i.e., Ai2, AiXplain, Explosion, John Snow Labs, Kaggle, Lightning AI), asking them to forward the survey to their users. As an incentive, we highlighted the potential insights that could be gained into the actual needs of users in supervised learning and AL. Although this approach yielded limited feedback only, it nevertheless contributed to the overall outreach effort. Positive responses were received from AL Toolbox, which forwarded the call to some of their annotators; Argilla, which permitted the call to be shared in the Hugging Face Discord channel; Explosion, which shared the call on LinkedIn; Labelbox, which forwarded the call internally; and Label Sleuth, which forwarded the call to their users.

In retrospect, we believe the limited engagement from tool providers and companies may be attributed to a combination of factors: an insufficiently compelling appeal or reward for sharing that we could provide from our side, the possibility that the survey was not a suitable fit for their interests, and the timing of the survey launch close to the Christmas and winter holiday period.

B.2 Survey Portal

The survey was conducted using LimeSurvey in version 3.27.4.

B.3 Participation and Completion Rates

The survey remained open for six weeks. According to question VII.7, mailing lists were the most effective referral source, with noticeable spikes in activity following each call (with declining impact). Given this pattern, and after three waves of invita-

tions, we did not expect a significant increase in responses by keeping the survey open longer.

Given that we have no information about the number of subscribers to the various mailing lists, or who we reached via social media or other means, it is impossible to determine how many individuals received the invitation to participate in the survey. According to LimeSurvey statistics, 1124 individuals clicked the survey link. Of these, 171 began the main content of the survey, and 144 completed it.

B.4 Data Protection

In consultation with data protection officers, we implemented measures to ensure compliance with the EU General Data Protection Regulation. The survey was conducted anonymously, with the option to provide an email address to receive the survey evaluation afterward. Free-form text fields (used for several single- and multiple-choice questions to provide additional answer options, as well as for general comments towards the end of the survey) constitute a gray area. This is because participants could potentially enter personally identifiable information, particularly when combined with the demographic data collected in question group VII. To meet legal obligations, we informed participants about how any potential personal data would be processed and concluded a joint-controller agreement among the institutions involved.

B.5 Anonymization for Dataset Release

For public release, text answers were manually processed as follows. We started from the raw dataset, excluding the separately stored email addresses.

The following steps were performed on each field: We replaced all mentions that could reveal the respondents' identities with placeholders. This includes URLs, links, email addresses, single words, sentences, and paragraphs. We also applied this to language mentions, as they could contribute to de-anonymization when combined with other fields (e.g., in case of languages that few people in the NLP community are researching). In this context, we took a conservative approach to V.2 (languages of the annotation project with AL) by removing all answers to preserve anonymity.

For question items containing highly specific information that may allow to draw conclusions about the respective participant, we replaced the entries with broader categories:

- **IV.1 (year):** 2020–2024, 2015–2019, 2010–

¹³<https://github.com/argilla-io/argilla>

¹⁴<https://github.com/cleanlab/cleanlab>

¹⁵<https://labelbox.com/>

¹⁶<https://labelstud.io/>

¹⁷<https://sourceforge.net/projects/mat-annotation/>

2014, 2005–2009

- **V.3 (hours):** up to 20, 21–50, 51–100, 101–500, more than 500
- **V.4 (instance count):** up to 100, 101–500, 501–1000, 1001–10,000, more than 10,000, N/A
- **V.4 (instance type):** documents, sentences, tokens, other, N/A
- **VII.5 (countries):** Africa, Asia, Europe, North America, Oceania, South America

As a final step, we separated responses and demographic information and shuffled rows randomly to prevent re-merging of the two files.

C Full Survey

Data Annotation Bottleneck & Active Learning for NLP in the Era of LLMs

The success of Natural Language Processing (NLP) often depends on the availability of (high-quality) data. In particular, **the costly manual annotation of text data has posed a major challenge since the early days of NLP**. To overcome the data annotation bottleneck, a number of methods have been proposed. One prominent method in this context is **Active Learning**, which aims to minimize the set of data that needs to be annotated.

However, the development of Large Language Models (LLMs) has changed the field of NLP considerably. For this reason, it is of huge interest to us working in this field (both in research and in practical application) to understand **if and how a lack of annotated data is still affecting NLP today**.

At the center of this survey is Active Learning, which was last surveyed in a [web survey in 2009](#). Fifteen years later, we aim to reassess the current state of the method from the user's point of view. Besides inquiring where Active Learning is used, we also ask where it is not used in favor of other methods. Moreover, we want to understand which computational methods the community considers most useful to overcome a lack of annotated data.

The survey is conducted solely for non-commercial, academic purposes. It specifically targets participants who are or have been involved in supervised machine learning for NLP. Knowledge about Active Learning is not required. Filling out the survey will take you approximately 15 minutes.

Why should I invest my time in this survey? We need your collective expertise in the field of NLP, Supervised Machine Learning, or Active Learning, to understand how recent advancements, such as LLMs, have changed the long-standing data annotation bottleneck. The results of this survey will help the community to better understand the state and open issues of contemporary Active Learning, and incorporate these insights into research and development of new methods and technologies. To this end, a study presenting and discussing the results of this survey will be published as an open access publication. If you wish to be notified upon publication, you can optionally enter your email address at the end of the

survey.

What is Active Learning? Active Learning is a method to create a small but meaningful annotated dataset with the goal of minimizing the annotation effort. It is an iterative cyclic method between a human annotator and a learning algorithm. In each iteration, an instance selection strategy (also referred to as query or acquisition strategy) is used to select data points that are considered particularly useful to be annotated next. These can be, for example (among many other strategies), the instances for which a machine learning model is most uncertain.

The survey is initiated by the researchers [*anonymized for review*]. If you have any questions, please contact us via [*anonymized for review*].

Consent, Data Usage, and Privacy

Declaration of Consent

[*not disclosed to ensure anonymity in the review*]

We need your consent before we can start collecting data for the survey.

- Yes, I would like to participate in this survey.
 No, I would not like to participate in this survey.

Data Usage and Privacy Information: We will store your provided answers on a server located in [*anonymized for review*]. After the survey has been conducted, we will process the collected data in order to investigate the research questions presented above to investigate if and how a lack of annotated data still affects the field of NLP in 2024. Our goal is to make the collected data available to the community under a [non-commercial share-alike CC BY-NC-SA 4.0 license](#). *The public dataset will be completely anonymous.* Any information in free text responses that could identify specific respondents will be removed before publication of the dataset. The processing of any personal data is detailed in privacy information in compliance with GDPR. This includes information on the purpose of data collection, how long we retain your data, your rights regarding your data, and how to contact us with any concerns.

We need your confirm that you have read and consented to the data usage and privacy information.

- I have read the information on data usage and privacy information and consent that my answers given in this survey will be stored and analyzed for research purposes as described above. I agree that my contribution will be made available to the community as part of a public dataset under CC BY-NC-SA 4.0 license. I hereby grant the authors permission to distribute my data under these terms. It will be ensured that no conclusions about individuals can be inferred from this data.

I. Relevance of Annotated Data in Light of Recent Advancements in NLP

This survey focuses on supervised learning in NLP, where annotated data is used to train machine learning models.

1. [sc,m]¹⁸ When applying NLP methods, have you ever encountered difficulties due to a lack of annotated data (e.g., you had to build a new dataset, without which the desired goal was unattainable)?

¹⁸Question properties: single choice (sc), multiple choice (mc), mandatory (m), and display conditional on previous response (c).

- (a) Yes
- (b) No [*directs participants to part VII.*]

You stated that you have had difficulties due to a lack of data.

2. [mc,m] Under what circumstances did you encounter difficulties due to lack of annotated data? Select all that apply.

- (a) When working on following under-resourced languages: [*text input*]
- (b) When working on a certain task (e.g., summarization): [*text input*]
- (c) When working with a specific requirement (e.g., on a problem with many classes): [*text input*]
- (d) Other: [*text input*]

Recent advancements, such as LLMs and Generative AI, have profoundly changed the NLP landscape. Considering these developments, do you think that a lack of annotated data is **currently** a problem? Please indicate below, how much you agree or disagree with each of these statements.

3. [sc,m] The type of tasks that I used to solve with supervised learning, can be (or will soon be) solved by leveraging generative AI to synthesize training data.

- Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)

4. [sc,m] Many problems will still be solved as supervised learning tasks.

- Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)

5. [sc,m] Annotated data is still a limiting factor in the context of supervised learning.

- Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)

6. [sc,m] Annotated data is still a limiting factor for the languages I work with.

- Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)

7. [sc,m] Annotated data is still a limiting factor for problems of a certain complexity (e.g., in summarization where summarizing long documents can be time-consuming).

- Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)

II. Overcoming a Lack of Annotated Data

Annotated data is required for supervised learning. In this section, we ask about methods to overcome a lack of data in such situations, and about your experiences with them.

1. [sc,m] Have you ever used a computational method to overcome a lack of annotated data?

- (a) Yes
- (b) No

2. [mc,m,c:II1] Please choose all computational methods that you have ever used to overcome a lack of annotated data.

- (a) Active Learning (e.g., to efficiently annotate data)

- (b) Data augmentation (e.g., to use existing training instances more efficiently)

- (c) Few-shot Learning (e.g., to achieve competitive results with only a few instances)

- (d) Semi-supervised Learning (e.g., use already annotated data for automatic labeling of training instances)

- (e) Text generation (e.g., to generate training instances)

- (f) Transfer learning (e.g., to use the pre-existing knowledge of already trained models)

- (g) Weak supervision (e.g., to programmatically obtain (pseudo-)annotated instances using, e.g., labeling functions)

- (h) Zero-shot (e.g., to work without any training data at all)

- (i) Other: [*text input*]

3. [mc,m,c:II1] What are the reasons why you have never used a computational method to overcome a lack of annotated data? Please choose all options that apply to you.

- (a) I have never heard of these methods.

- (b) I never coordinated an annotation project.

- (c) We had enough human resources to annotate our data.

You stated that you have used a method other than Active Learning.

4. [sc,m,c:II2] Did you consider your chosen computational method(s) to overcome a lack of annotated data to be successful?

- Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)

5. [mc,m,c:II2] What are the specific reasons for not applying Active Learning? Please select all that apply.

- (a) Never heard of Active Learning.

- (b) Insufficient expertise/knowledge.

- (c) Did not want to spend overhead in implementing an Active Learning-based annotation environment.

- (d) Did not know of any suitable annotation tools that easily integrate Active Learning.

- (e) Did not meet my project's specific requirements.

- (f) Wanted to avoid sampling bias in the corpus.

- (g) Was not convinced that Active Learning would reduce annotation cost.

- (h) Did not use Active Learning because I couldn't estimate upfront its impact on reducing annotation costs.

- (i) Other: [*text input*]

6. [m,c:II5] Why did Active Learning not fit your specific requirements? [*text input*]

7. [sc,m,c:II2] Would you consider applying Active Learning in future annotation projects?

- (a) Yes

- (b) No

- (c) I don't know enough about Active Learning to answer this question.

- (d) Only under specific circumstances: [*text input*]

8. [mc,m,c:II7] What are the reasons why you would not apply Active Learning in future annotation projects?
 - (a) Active Learning has become obsolete nowadays.
 - (b) Active Learning is a useful concept in theory but does not work well enough in practice.
 - (c) Other: *[text input]*

[directs participants who never used Active Learning to part VII.]

III. Active Learning – General

In this section, we want to learn more about your experience with Active Learning.

1. [mc,m] What is your expertise with Active Learning?
 - (a) I have been part of an Active Learning workflow as an annotator.
 - (b) I have organized an Active Learning annotation workflow.
 - (c) I have knowledge about instance selection strategies in Active Learning but use pre-built solutions.
 - (d) I have implemented Active Learning strategies or workflows.
 - (e) I have researched Active Learning.
2. [mc,m] What was your primary motivation to use Active Learning?
 - (a) Obtain annotated data at minimal annotation costs
 - (b) Gather experience with practical applications of Active Learning
 - (c) Test your annotation guidelines to identify difficult examples
 - (d) Other: *[text input]*

In the following questions, we sometimes ask about (*annotation*) *instances*, by which we mean the entities to be annotated, such as documents, words, or sentences.

3. [mc,m] What obstacles have you encountered when applying Active Learning?
 - (a) Finding annotators that achieve satisfactory performance
 - (b) Performing Active Learning with multiple annotators (e.g., distributing work, resolving disagreement)
 - (c) Unclear instructions how to annotate (lack of annotation guidelines)
 - (d) Hard cases for annotation (undecidable, ambiguous, subjective)
 - (e) Lack of resources (GPU/TPU)
 - (f) Choice of model and instance selection algorithm
 - (g) Choice of stopping criterion
 - (h) Other: *[text input]*
4. [sc,m] Between two iterations of Active Learning, a new model is usually trained. This new model is then used to select new examples for annotation. What is the maximum time you would be willing to wait between two annotation cycles?
 - (a) Less than a minute
 - (b) 1 minute to less than 10 minutes
 - (c) 10 minutes to less than 1 hour
 - (d) 1 hour to less than 10 hours
 - (e) 10 hours to less than 1 day

- (f) 1 day to less than 1 week
- (g) I will wait long as it takes

5. [mc,m] In which scenario(s) have you worked with Active Learning?

- (a) In a lab setting with simulated annotators
- (b) In an applied setting with human annotators

[directs participants that never used Active Learning in an applied setting to part VI.]

IV. Active Learning – Methodological Setup

The following questions relate to type and scope of a previous annotation project in which you employed Active Learning.

In case you performed more than one such annotation project, please think of your **most recent project** with Active Learning when answering the following questions.

1. [m] In which year did the project start? *[text input]*
2. [sc,m] Which type of machine learning model was trained during Active Learning?
 - (a) Classic (Naive Bayes, Support Vector Machine, Conditional Random Fields, ...)
 - (b) Neural Network (Convolutional Neural Network, Long Short-term Memory, ...)
 - (c) BERT era Language Models such as BERT, GPT-2, RoBERTa, ...
 - (d) Large Language Models such as Phi-3, Llama, Mistral, Gemma, Gemini, GPT-3/4, ...
 - (e) Do not know
 - (f) Other: *[text input]*
3. [sc,m] What instance selection strategy¹⁹ have you used during Active Learning? If you have tried different strategies, please indicate the strategy that you eventually decided on.
 - (a) Uncertainty-based²⁰
 - (b) Disagreement-based²¹
 - (c) Gradient information-based²²
 - (d) Performance prediction-based²³
 - (e) Density-based²⁴

¹⁹ Tooltip: The most salient component of an Active Learning setup is the instance selection strategy, which decides on the instances to be labeled next.

²⁰ Tooltip: Selects instances for which the model is most uncertain. Examples are least-confidence, entropy and margin-sampling.

²¹ Tooltip: Uses multiple models to select instances based on disagreement between model outputs. A popular example is query-by-committee.

²² Tooltip: Selects instances based on their impact on the model. The impact is measured by, e.g., the norm of the gradients. A popular example is expected gradient length.

²³ Tooltip: Selects instances that have the most potential of reducing future errors. Examples are policy-learning strategies with reinforcement learning or imitation learning, and cartography Active Learning.

²⁴ Tooltip: Selects instances that are representative of dense regions in the embedding space. Density-based representatives can be selected, e.g., based on n-gram counts.

- (f) Discriminative-based²⁵
 - (g) Batch diversity²⁶
 - (h) Hybrid (Combines different of the aforementioned concepts.)
 - (i) Do not know
 - (j) Other: *[text input]*
4. [sc,m] Between two iterations of Active Learning, a new model is usually trained. This new model is then used to select new examples for annotation. How long was the resulting waiting time for the annotator in your scenario on average? Please select the matching time interval.
- (a) We did not retrain
 - (b) Less than a minute
 - (c) 1 minute to less than 10 minutes
 - (d) 10 minutes to less than 1 hour
 - (e) 1 hour to less than 10 hours
 - (f) 10 hours to less than 1 day
 - (g) 1 day to less than 1 week
 - (h) Do not know
5. [sc,m] How did you decide when to stop the Active Learning process?
- (a) Evaluation of the learned model on a held-out gold standard
 - (b) Money and/or time available for annotation were depleted
 - (c) All relevant documents annotated
 - (d) The stopping time was indicated by an algorithmic stopping criterion (for example based on the current model's performance)
 - (e) Do not know
 - (f) Other: *[text input]*

V. Active Learning – Task & Annotation Setup

The following questions relate to type and scope of a previous annotation project of your choice, where Active Learning was employed.

In case you performed more than one such annotation project, please think of your **most recent project** with Active Learning when answering the following questions.

1. [sc,m] What specific NLP task did you collect annotations for?
- (a) Automatic speech recognition
 - (b) Coreference resolution
 - (c) Chunking
 - (d) Information extraction
 - (e) Language generation
 - (f) Language understanding
 - (g) Machine translation
 - (h) Morphological analysis
 - (i) Named entity recognition
 - (j) Part-of-speech tagging
2. [mc,m] What was the language of the texts that were annotated? (If multilingual, select multiple options.)
- (a) Arabic
 - (b) English
 - (c) French
 - (d) German
 - (e) Hindi
 - (f) Mandarin
 - (g) Spanish
 - (h) Other: *[text input]*
3. [sc,m] How much time was spent on annotation in total? In the case of multiple annotators, please enter the total sum of hours worked by the annotators.
- (a) *[text input]* hours
 - (b) Do not know
4. [m] What was the size of the resulting annotated corpus in terms of annotated instances? Please provide the annotation instance type in brackets, e.g. 1000 (tokens), 100 (sentences), or 10 (documents).. *[text input]*
5. [mc,m] Who were your annotators?
- (a) Annotation was done by the project coordinators or other project members (data scientist / linguist roles or similar)
 - (b) Domain experts
 - (c) Non-domain experts
 - (d) Other: *[text input]*
6. [sc,m] Did you use an annotation tool with Active Learning support?
- (a) Yes
 - (b) No
7. [sc,m,c:V6] Which annotation tool with Active Learning support did you use?
- (a) ActiveAnno
 - (b) Argilla
 - (c) AWS Sagemaker Ground Truth
 - (d) AWS Comprehend
 - (e) BioQRator
 - (f) INCEpTION
 - (g) Labelbox
 - (h) Label Studio
 - (i) MAT
 - (j) Potato
 - (k) Prodigy
 - (l) Other: *[text input]*

²⁵Tooltip: Selects instances that differ from already annotated instances. Examples are selecting discriminative-based representatives based on rare words or a lesser similarity to the already annotated instances, as well as the use of discriminative Active Learning.

²⁶Tooltip: Selects a batch of instances that are diverse. Examples are coresets, BADGE and ALPS.

8. [sc,m] In annotation, what did you do with data points that were ambiguous (i.e., caused disagreement between multiple annotators)?
- (a) Deleted them
 - (b) Assigned one of two labels
 - (c) Not applicable, each instance had at most one annotation.
 - (d) Other: *[text input]*
9. [sc,m] While using Active Learning, did you have to change the annotation schema due to challenging examples surfaced during the annotation process (eg, add new classes in a classification task)?
- (a) No
 - (b) Yes
10. [sc,m,c:V9] What did you do with previously annotated examples?
- (a) Previously annotated examples were re-annotated.
 - (b) Previously annotated examples were left unchanged.
 - (c) Other: *[text input]*
11. [sc,m] Did you consider your annotation project to be successful?
- Very successful, Successful, Neither unsuccessful nor successful, Unsuccessful, Very unsuccessful (*5-point Likert scale*)
12. [sc,m] Was the use of Active Learning as effective as intended?
- Very effective, Effective, Neither effective nor ineffective, Ineffective, Very Ineffective (*5-point Likert scale*)
13. [mc,m,c:V12] What were the reasons that reduced the effectiveness of Active Learning in your case of application? Please choose all options that apply.
- (a) In retrospect, I had insufficient expertise/knowledge.
 - (b) Overhead in setting up an Active Learning-based annotation environment.
 - (c) Lack of suitable annotation tools that easily integrate Active Learning.
 - (d) In retrospect, Active Learning did not meet my project's specific requirements.
 - (e) Active Learning created a sampling bias in the corpus.
 - (f) Active Learning did not reduce annotation cost.
 - (g) Active Learning did not work well in my scenario.
 - (h) My upfront estimation of the impact on reducing annotation costs was not accurate.
 - (i) The dependency of the model from the created dataset and vice versa.
 - (j) Other: *[text input]*
14. [sc,m] Would you consider applying Active Learning again in future annotation projects?
- (a) No
 - (b) Yes
 - (c) Other: *[text input]*
15. [mc,c:V14] Why would you not consider Active Learning in future annotation projects?
- (a) Active Learning has become obsolete nowadays.
 - (b) Active Learning is a useful concept in theory but does not work well enough in practice.
 - (c) Other: *[text input]*

VI. Trends in Active Learning for NLP

In this section, we are interested in your opinion on whether the technological and methodological developments have affected the field of Active Learning, and what you think is still missing.

Please indicate how much you agree or disagree with the following statements:

1. [sc,m] Text embeddings are crucial for many methods in Active Learning for NLP.
 - Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)
2. [sc,m] GPU-accelerated computing has changed the choice of model in Active Learning for NLP.
 - Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)
3. [sc,m] Neural Networks have changed the choice of instance selection strategy in Active Learning for NLP.
 - Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)
4. [sc,m] LLMs (with 1B parameters or more) are frequently used in Active Learning for NLP.
 - Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree (*5-point Likert scale*)
5. What are obvious next developments for Active Learning in NLP that you believe will have a big impact on the field? *[text input]*

VII. Background Information

You are almost done. We just need a few more basic pieces of information about you in order to put your answers into context.

1. [mc] Where are you currently working? Please choose all options that apply to you.
 - (a) Academia
 - (b) Industry
 - (c) Governmental organization
 - (d) Other: *[text input]*
2. [mc] What is your education background? Please choose all options that apply to you.
 - (a) Linguistics
 - (b) Computational Linguistics
 - (c) Computer Science/Informatics
 - (d) Engineering
 - (e) Mathematics
 - (f) Social Sciences
 - (g) Other: *[text input]*
3. [mc] Which field are you currently working in? Please choose all options that apply to you.
 - (a) Economics

- (b) Education
- (c) Financial sector
- (d) Health services sector
- (e) Humanities
- (f) Information and communications technology
- (g) Legal sector
- (h) Public service sector
- (i) Society and politics
- (j) Other: *[text input]*

4. [sc] How many years of experience do you have in Machine Learning/NLP?
 - (a) Up to 1 year
 - (b) 1-2 years
 - (c) 3-5 years
 - (d) 5-10 years
 - (e) More than 10 years
5. [sc] Which country is your primary place of residence?
 - (a) *Dropdown menu with 196 country names*
 - (b) Other: *[text input]*
6. Do you have any comments on the survey? *[text input]*
7. [sc] How did you become aware of the survey?
 - (a) Social media (e.g., Facebook, Twitter, Instagram)
 - (b) Personalized email invitation
 - (c) Mailing list (e.g., ACL Member Portal)
 - (d) Friend, colleague, or peer shared it
 - (e) Other: *[text input]*

D Results

D.1 Overview of Responses

Table 3 provides a full overview of survey participants' responses to the predefined options for all 52 questions.

D.2 Additional Details

Contemporary waiting times Figure 9 illustrates the waiting times (corresponding to sampling times) for annotation cycles in practice (considering the 33 recent applied AL projects; cf. IV.4), and how this relates to the general perception of what is acceptable (reported by all AL users, lab and applied, in III.4).

D.3 Sector-specific Analysis of Reasons for Reduced Effectiveness of Active Learning

We explore group-specific differences in the reasons for a reduced effectiveness of AL in 23 recent projects (cf. V.13, 2020 onward), focusing on the sector of work.

The sample includes two almost equally sized groups: 11 respondents from academia and 13 respondents from industry (with 2 overlapping). One

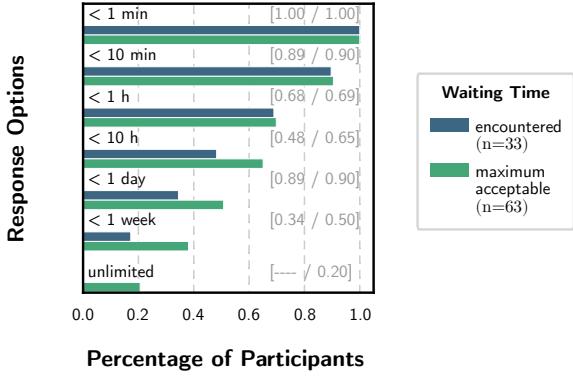


Figure 9: Maximum acceptable as opposed to last encountered waiting times (if applicable).

additional respondent is from the government sector, which is excluded from the following analysis. Table 2 provides an overview of the response patterns. Overall, both groups exhibit similar tendencies in the yes/no responses. Especially, for the lack of suitable annotation tools (c), unmet project-specific requirements (d), and sampling bias (e), the mean values in the sample at hand are closely aligned between academia and industry (0.33 and 0.27, 0.11 and 0.09, 0.22 and 0.18, respectively). Slightly more difference can be observed in a lack (c) or inaccurate upfront estimation (h) of cost reduction, with no academic respondents indicating this issue, compared to a mean of 0.18 for industry respondents. In contrast, model-dependency of datasets seems to be more of a concern in academia.

At this point, we refrain from applying significance tests due to the small sample size, which limits the generalizability of the observations and, thus, the informative value of such analysis.

VARIABLE	ACADEMIA			INDUSTRY		
	# no	# yes	μ_{yes}	# no	# yes	μ_{yes}
Insufficient expertise (a)	7	2	0.22	10	1	0.09
Overhead in setup (b)	5	4	0.44	8	3	0.27
Lack of annotation tools (c)	6	3	0.33	8	3	0.27
Project-specific requirements (d)	8	1	0.11	10	1	0.09
Sampling bias (e)	7	2	0.22	9	2	0.18
No cost reduction (f)	9	0	0.00	9	2	0.18
Did not work well (g)	6	3	0.33	9	2	0.18
Inaccurate upfront estimation (h)	9	0	0.00	9	2	0.18
Dataset-model dependency (i)	6	3	0.33	10	1	0.09

Table 2: Predefined reason selection for reduced effectiveness in AL (V.13) in the practical projects in recent years (2020 onward) across academia and industry. For both groups, we show the frequency of no (# no; the respective reason did not affect the effectiveness of AL) and yes answers (# yes; the respective reason affected the effectiveness of AL), as well as the mean of yes answers (μ_{yes}). We assume mutually exclusive groups for the sake of comparison and exclude the two overlapping cases, resulting in 9 respondents from academia and 11 from industry.

SURVEY QUESTION	MAPPING TO RQ	n	RESPONSES (TOTAL / PERCENTAGE OF PARTICIPANTS)
I.1	RQ1	144	Yes (138 / 96%), No (6 / 4%)
I.2	RQ1	138	When working on following under-resourced languages (77 / 56%), When working on a certain task (96 / 70%), When working with a specific requirement (71 / 51%), Other (119 / 86%)
I.3	RQ1	138	Strongly agree (3 / 2%), Agree (38 / 28%), Neither agree nor disagree (38 / 28%), Disagree (39 / 28%), Strongly disagree (20 / 14%)
I.4	RQ1	138	Strongly agree (35 / 25%), Agree (75 / 54%), Neither agree nor disagree (18 / 13%), Disagree (8 / 6%), Strongly disagree (2 / 1%)
I.5	RQ1	138	Strongly agree (59 / 43%), Agree (71 / 51%), Neither agree nor disagree (6 / 4%), Disagree (1 / 1%), Strongly disagree (1 / 1%)
I.6	RQ1	138	Strongly agree (51 / 37%), Agree (53 / 38%), Neither agree nor disagree (25 / 18%), Disagree (8 / 6%), Strongly disagree (1 / 1%)
I.7	RQ1	138	Strongly agree (62 / 45%), Agree (63 / 46%), Neither agree nor disagree (11 / 8%), Disagree (1 / 1%), Strongly disagree (1 / 1%)
II.1	RQ2	138	Yes (120 / 87%), No (18 / 13%)
II.2	RQ2	120	Active Learning (63 / 53%), Data augmentation (88 / 73%), Few-shot Learning (75 / 63%), Semi-supervised Learning (64 / 53%), Text generation (59 / 49%), Transfer learning (79 / 66%), Weak supervision (53 / 44%), Zero-shot (63 / 53%), Other (14 / 12%)
II.3*	RQ2	18	I have never heard of these methods. (10 / 56%), I never coordinated an annotation project. (6 / 33%), We had enough human resources to annotate our data (5 / 28%).
II.4	RQ2	56 ²⁷	Strongly agree (4 / 7%), Agree (28 / 50%), Neither agree nor disagree (21 / 38%), Disagree (2 / 4%), Strongly disagree (1 / 2%)
II.5	RQ2, RQ5	57	Never heard of Active Learning. (14 / 25%), Insufficient expertise / knowledge. (28 / 49%), Did not want to spend overhead in implementing an Active Learning-based annotation environment. (21 / 37%), Did not know of any suitable annotation tools that easily integrate Active Learning. (18 / 32%), Did not meet my project's specific requirements. (5 / 9%), Wanted to avoid sampling bias in the corpus. (10 / 18%), Was not convinced that Active Learning would reduce annotation cost. (14 / 25%), Did not use Active Learning because I couldn't estimate upfront its impact on reducing annotation costs. (12 / 21%), Other (9 / 16%)
II.6*	RQ2, RQ5	5	<i>free text answer</i> (5 / 100%)
II.7	RQ2, RQ5	56	Yes (30 / 54%), No (1 / 2%), I don't know enough about Active Learning to answer this question. (21 / 38%), Only under specific circumstances (4 / 7%)

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²⁷One participant was not directed to this question after choosing solely “Other” in II.2. This applies also for II.7.

Table 3 – continued from previous page

SURVEY QUESTION	MAPPING TO RQ	n	RESPONSES (TOTAL / PERCENTAGE OF PARTICIPANTS)
II.8	RQ2	1	Active Learning has become obsolete nowadays. (0 / 0%), Active Learning is a useful concept in theory but does not work well enough in practice. (1 / 100%), Other (0 / 0%)
III.1*	RQ2, RQ3	63	I have been part of an Active Learning workflow as an annotator. (24 / 38%), I have organized an Active Learning annotation workflow. (38 / 60%), I have knowledge about instance selection strategies in Active Learning but use pre-built solutions. (28 / 44%), I have implemented Active Learning strategies or workflows. (45 / 71%), I have researched Active Learning. (43 / 68%)
III.2	RQ2, RQ5	63	Obtain annotated data at minimal annotation costs (55 / 87%), Gather experience with practical applications of Active Learning (29 / 46%), Test your annotation guidelines to identify difficult examples (15 / 24%), Other (5 / 8%)
III.3	RQ2	63	Finding annotators that achieve satisfactory performance (22 / 35%), Performing Active Learning with multiple annotators (35 / 56%), Unclear instructions how to annotate (18 / 29%), Hard cases for annotation (37 / 59%), Lack of resources (16 / 25%), Choice of model and instance selection algorithm (31 / 49%), Choice of stopping criterion (22 / 35%), Other (4 / 6%)
III.4**	RQ3	63	Less than a minute (6 / 10%), 1 minute to less than 10 minutes (13 / 21%), 10 minutes to less than 1 hour (3 / 5%), 1 hour to less than 10 hours (9 / 14%), 10 hours to less than 1 day (8 / 13%), 1 day to less than 1 week (11 / 17%), I will wait long as it takes (13 / 21%)
III.5	RQ3	63	In a lab setting with simulated annotators (36 / 57%), In an applied setting with human annotators (48 / 76%)
IV.1**²⁸	RQ3	48	<i>free text answer</i> (47 / 98%), No answer (1 / 2%)
IV.2²⁹	RQ3, RQ5	48	Classic (11 / 23%), Neural Network (5 / 8%), BERT era Language Models such as BERT, GPT-2, RoBERTa, ... (24 / 50%), Large Language Models such as Phi-3, Llama, Mistral, Gemma, Gemini, GPT-3/4, ... (2 / 4%), Do not know (2 / 4%), Other (4 / 8%)
		33	Classic (3 / 9%), Neural Network (4 / 12%), BERT era Language Models such as BERT, GPT-2, RoBERTa, ... (20 / 61%), Large Language Models such as Phi-3, Llama, Mistral, Gemma, Gemini, GPT-3/4, ... (2 / 6%), Do not know (2 / 6%), Other (2 / 6%)
IV.3	RQ3, RQ5	48	Uncertainty-based (20 / 42%), Disagreement-based (6 / 13%), Gradient information-based (2 / 4%), Performance prediction-based (5 / 10%), Density-based (1 / 2%), Discriminative-based (0 / 0%), Batch diversity (1 / 2%), Hybrid (7 / 15%), Do not know (4 / 8%), Other (2 / 4%)
		33	Uncertainty-based (13 / 39%), Disagreement-based (5 / 15%), Gradient information-based (2 / 6%), Performance prediction-based (4 / 12%), Density-based (1 / 3%), Discriminative-based (0 / 0%), Batch diversity (1 / 3%), Hybrid (3 / 9%), Do not know (3 / 9%), Other (1 / 3%)
IV.4**	RQ3	48	We did not retrain (0 / 0%), Less than a minute (8 / 17%), 1 minute to less than 10 minutes (8 / 17%), 10 minutes to less than 1 hour (6 / 13%), 1 hour to less than 10 hours (8 / 17%), 10 hours to less than 1 day (6 / 13%), 1 day to less than 1 week (6 / 13%), Do not know (6 / 13%)
		33	We did not retrain (0 / 0%), Less than a minute (3 / 10%), 1 minute to less than 10 minutes (6 / 21%), 10 minutes to less than 1 hour (6 / 21%), 1 hour to less than 10 hours (4 / 14%), 10 hours to less than 1 day (5 / 17%), 1 day to less than 1 week (5 / 17%), Do not know (4 / 0%)
IV.5	RQ3, RQ5	48	Evaluation of the learned model on a held-out gold standard (15 / 31%), Money and/or time available for annotation were depleted (18 / 38%), All relevant documents annotated (4 / 8%), The stopping time was indicated by an algorithmic stopping criterion (6 / 13%), Do not know (2 / 4%), Other (3 / 6%)

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²⁸The years of project start in the free text answer are: 2020–2024 (33), 2015–2019 (11), 2010–2014 (2), 2005–2009 (1).

²⁹For the paper, we refined the wording by replacing “classic models” with “traditional models”.

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SURVEY QUESTION	MAPPING TO RQ	n	RESPONSES (TOTAL / PERCENTAGE OF PARTICIPANTS)
		33	Evaluation of the learned model on a held-out gold standard (10 / 30%), Money and/or time available for annotation were depleted (13 / 39%), All relevant documents annotated (2 / 6%), The stopping time was indicated by an algorithmic stopping criterion (4 / 12%), Do not know (1 / 3%), Other (3 / 9%)
V.1* ³⁰	RQ3, RQ5	48	Automatic speech recognition (0 / 0%), Coreference resolution (1 / 2%), Chunking (0 / 0%), Information extraction (5 / 10%), Language generation (0 / 0%), Language understanding ((0 / 0%)), Machine translation (3 / 6%), Morphological analysis (0 / 0%), Named entity recognition (5 / 10%), Part-of-speech tagging (0 / 0%), Question answering (0 / 0%), Relation extraction (1 / 2%), Semantic similarity (0 / 0%), Sentiment analysis (3 / 6%), Syntactic parsing (1 / 2%), Summarization (0 / 0%), Text categorization (22 / 46%), Word segmentation (0 / 0%), Word sense disambiguation (0 / 0%), Other (7 / 15%)
V.2* ³¹	RQ3, RQ5	48	Arabic (4 / 8%), English (32 / 67%), French (5 / 10%), German (10 / 21%), Hindi (1 / 1%), Mandarin (1 / 2%), Spanish (6 / 13%), Other (16 / 33%)
V.3*	RQ3, RQ5	48	<i>Indication of hours</i> (22 / 46%), Do not know (26 / 54%)
V.4*	RQ3, RQ5	48	<i>free text answer</i> (48 / 100%)
V.5*	RQ3	48	Annotation was done by the project coordinators or other project members (20 / 42%), Domain experts (29 / 60%), Non-domain experts (12 / 25%), Other (3 / 6%)
V.6	RQ3	48	Yes (25 / 52%), No (23 / 48%)
		33	Yes (17 / 52%), No (16 / 48%)
V.7 ³²	RQ3	25	ActiveAnno (1 / 4%), Argilla (4 / 16%), AWS Sagemaker Ground Truth (0 / 0%), AWS Comprehend (0 / 0%), BioQRator (0 / 0%), INCEpTION (2 / 8%), Labelbox (0 / 0%), Label Studio (1 / 4%), MAT (0 / 0%), Potato (0 / 0%), Prodigy (2 / 8%), Other (15 / 31%)
		17	ActiveAnno (1 / 6%), Argilla (4 / 24%), AWS Sagemaker Ground Truth (0 / 0%), AWS Comprehend (0 / 0%), BioQRator (0 / 0%), INCEpTION (0 / 0%), Labelbox (0 / 0%), Label Studio (1 / 6%), MAT (0 / 0%), Potato (0 / 0%), Prodigy (2 / 12%), Other (9 / 53%)
V.8*	RQ3	48	Deleted them (6 / 13%), Assigned one of two labels (14 / 29%), Not applicable, each instance had at most one annotation. (15 / 31%), Other (13 / 27%)
V.9*	RQ3	48	No (27 / 56%), Yes (21 / 44%)
V.10*	RQ3	21	Previously annotated examples were re-annotated. (12 / 57%), Previously annotated examples were left unchanged. (6 / 29%), Other (3 / 14%)
V.11	RQ3	48	Very successful (7 / 15%), Successful (35 / 73%), Neither successful nor unsuccessful (6 / 13%), Unsuccessful (0 / 0%), Very unsuccessful (0 / 0%)
		33	Very successful (6 / 18%), Successful (24 / 73%), Neither successful nor unsuccessful (3 / 9%), Unsuccessful (0 / 0%), Very unsuccessful (0 / 0%)
V.12	RQ3, RQ5	48	Very effective (12 / 25%), Effective (19 / 40%), Neither effective nor ineffective (14 / 29%), Ineffective (2 / 4%), Very ineffective (1 / 2%)
		33	Very effective (10 / 30%), Effective (12 / 36%), Neither effective nor ineffective (8 / 24%), Ineffective (2 / 6%), Very ineffective (1 / 3%)

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³⁰We updated the 2009 task selection (Tomanek and Olsson, 2009) based on <http://nlpexplorer.org/> and Hou et al. (2021).

³¹We adopted the language selection for this question from Tomanek and Olsson (2009).

³²We based the list of annotation tools on Borisova et al. (2024). For n = 48, in addition to 7 self-built solutions, participant-added options emphasize further relevant tools: LabelSleuth (4; Shnarch et al., 2022a), AL Toolbox (2; Tsvigun et al., 2022b), ALAMBIC (1; Nachtegael et al., 2023a), and ALANNO (1; Jukić et al., 2023). For n = 33, in addition to 4 self-built solutions, participant-added options emphasize further relevant tools: LabelSleuth (3), ALAMBIC (1), and ALANNO (1).

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SURVEY QUESTION	MAPPING TO RQ	n	RESPONSES (TOTAL / PERCENTAGE OF PARTICIPANTS)
V.13	RQ3, RQ5	36	In retrospect, I had insufficient expertise/knowledge. (6 / 17%), Overhead in setting up an Active Learning-based annotation environment. (10 / 28%), Lack of suitable annotation tools that easily integrate Active Learning. (11 / 31%), In retrospect, Active Learning did not meet my project's specific requirements. (2 / 6%), Active Learning created a sampling bias in the corpus. (6 / 17%), Active Learning did not reduce annotation cost. (4 / 11%), Active Learning did not work well in my scenario. (7 / 19%), My upfront estimation of the impact on reducing annotation costs was not accurate. (5 / 14%), The dependency of the model from the created dataset and vice versa. (7 / 19%), Other (8 / 22%)
		23	In retrospect, I had insufficient expertise/knowledge. (3 / 9%), Overhead in setting up an Active Learning-based annotation environment. (7 / 21%), Lack of suitable annotation tools that easily integrate Active Learning. (8 / 24%), In retrospect, Active Learning did not meet my project's specific requirements. (2 / 6%), Active Learning created a sampling bias in the corpus. (5 / 15%), Active Learning did not reduce annotation cost. (3 / 9%), Active Learning did not work well in my scenario. (7 / 21%), My upfront estimation of the impact on reducing annotation costs was not accurate. (3 / 9%), The dependency of the model from the created dataset and vice versa. (5 / 15%), Other (4 / 12%)
V.14	RQ3, RQ5	48	No (2 / 4%), Yes (42 / 88%), Other (4 / 8%)
		33	No (2 / 6%), Yes (28 / 85%), Other (3 / 9%)
V.15	RQ3, RQ5	2	Active Learning has become obsolete nowadays. (0 / 0%), Active Learning is a useful concept in theory but does not work well enough in practice. (2 / 100%), Other (0 / 0%)
		2	Active Learning has become obsolete nowadays. (0 / 0%), Active Learning is a useful concept in theory but does not work well enough in practice. (2 / 100%), Other (0 / 0%)
VI.1	RQ4	63	Strongly agree (22 / 35%), Agree (29 / 46%), Neither agree nor disagree (10 / 16%), Disagree (1 / 2%), Strongly disagree (1 / 2%)
VI.2	RQ4	63	Strongly agree (15 / 24%), Agree (27 / 43%), Neither agree nor disagree (17 / 27%), Disagree (2 / 3%), Strongly disagree (2 / 3%)
VI.3	RQ4	63	Strongly agree (15 / 24%), Agree (22 / 35%), Neither agree nor disagree (19 / 30%), Disagree (6 / 10%), Strongly disagree (1 / 2%)
VI.4	RQ4	63	Strongly agree (11 / 17%), Agree (12 / 19%), Neither agree nor disagree (28 / 44%), Disagree (9 / 14%), Strongly disagree (3 / 5%)
VI.5	RQ4	63	<i>free text answer</i> (26 / 41%), No answer (37 / 59%)
VII.1	background	144	Academia (107 / 74%), Industry (45 / 31%), Governmental organization (7 / 5%), Other (2 / 1%)
VII.2	background	144	Linguistics (27 / 19%), Computational Linguistics (56 / 39%), Computer Science/Informatics (88 / 61%), Engineering (23 / 16%), Mathematics (10 / 7%), Social Sciences (14 / 10%), Other (6 / 4%)
VII.3	background	144	Economics (4 / 3%), Education (44 / 31%), Financial sector (5 / 3%), Health services sector (12 / 8%), Humanities (24 / 17%), Information and communications technology (79 / 55%), Legal sector (8 / 6%), Public service sector (11 / 8%), Society and politics (7 / 5%), Other (18 / 13%)
VII.4	background	144	Up to 1 year (1 / 1%), 1-2 years (11 / 8%), 3-5 years (47 / 33%), 5-10 years (55 / 38%), More than 10 years (30 / 21%)
VII.5	background	144	<i>Indication of country</i> (143 / 99%), Other (0 / 0%), No answer (1 / 1%)
VII.6*	background	144	<i>free-text answer</i> (22 / 15%), No answer (122 / 85%)

VII.7**	background	144	Social media (16 / 11%), Personalized email invitation (33 / 23%), Mailing list (73 / 51%), Friend, colleague, or peer shared it (13 / 9%), Other (6 / 4%), No answer (3 / 2%)
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Table 3: Overview of response selection. Each survey question is linked to a research question. We indicate the number of participants n per question and their distribution across predefined response options. In case of questions described in Section 4.4, we provide both the full set of respondents ($n = 48$) and the set of respondents that started the reported AL project in 2020 or later ($n = 33$, marked in bold). Free-text responses are omitted for scope but can be seen in the dataset, provided in the supplementary material. *: marks questions not discussed in the main body of the paper, **: marks questions only discussed partly.