Collecting Cost-Effective, High-Quality Truthfulness Assessments with LLM Summarized Evidence

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Abstract

With the degradation of guardrails against mis- and disinformation online, it is more critical than ever to be able to effectively combat it. In this paper, we explore the efficiency and effectiveness of using crowd-sourced truthfulness assessments based on condensed, large language model (LLM) generated summaries of online sources. We compare the use of generated summaries to the use of original web pages in an A/B testing setting, where we employ a large and diverse pool of crowd-workers to perform the truthfulness assessment. We evaluate the quality of assessments, the efficiency with which assessments are performed, and the behavior and engagement of participants. Our results demonstrate that the Summary modality, which relies on summarized evidence, offers no significant change in assessment accuracy over the Standard modality, while significantly increasing the speed with which assessments are performed. Workers using summarized evidence produce a significantly higher number of assessments in the same time frame, reducing the cost needed to acquire truthfulness assessments. Additionally, the Summary modality maximizes both the inter-annotator agreements as well as the reliance on and perceived usefulness of evidence, demonstrating the utility of summarized evidence without sacrificing the quality of assessments.

1 Introduction

The proliferation of online misinformation has made truthfulness assessment a crucial task in the digital era. Fact-checking efforts, traditionally conducted by experts, have faced challenges in scalability and timeliness as the volume of information continues to grow [4]. Recent developments, such as X and Meta scaling down their reliance on paid fact-checkers, further highlight the urgency of scalable and efficient truthfulness assessment methods. As social media platforms reduce investments in professional fact-checking, alternative approaches become increasingly vital for addressing the growing volume of online misinformation. To address this, crowdsourcing has emerged as a promising alternative, leveraging the collective efforts of non-expert workers to evaluate truthfulness efficiently [32, 43]. However, the success of crowdsourced truthfulness assessments relies heavily on the format, presentation, and quality of evidence provided to participants. The choice of evidence itself, along with how it is presented, directly influences workers' ability to make accurate and reliable judgments.

Recent advancements in Large Language Models (LLMs) have opened new possibilities for improving the efficiency of truthfulness assessments by generating summarized evidence from lengthy documents. These models can distill essential information into concise formats, potentially reducing cognitive load and speeding up decision-making for crowd workers. Summarization also allows workers to process more evidence in less time, which is particularly valuable in large-scale annotation tasks. However, the adoption of LLM-generated summaries introduces its own set of challenges, including the risk of omitting critical details, introducing biases, or oversimplifying nuanced arguments. While summarized evidence could offer advantages in terms of efficiency and scalability, it may also affect the quality of truthfulness assessments. Workers might rely too heavily on the condensed summaries, overlooking important context available in full-length documents. Additionally, inconsistencies or factual errors introduced during the summarization process could inadvertently mislead workers, potentially

¹https://www.nytimes.com/2025/01/07/business/meta-community-notes-x.html.

impacting the reliability of their assessments. These trade-offs necessitate a thorough investigation into both the benefits and limitations of using LLM-generated summaries in crowdsourced truthfulness evaluations.

In this work, we focus on comparing two approaches: a *Standard* modality, where participants evaluate full-length webpages, and a *Summary* modality, where participants assess summarized evidence generated by a state-of-the-art LLM. The summarized format aims to reduce cognitive load and improve worker efficiency by condensing essential information while preserving factual accuracy. This presentation allows participants to process more information in less time, increasing overall throughput. Such improvements not only offer productivity gains but also translate into significant cost savings for large-scale annotation tasks, making summarization particularly valuable. However, the effectiveness and trade-offs of these two modalities remain an open question, which we address through a detailed empirical comparison using an A/B testing framework. This experimental design allows us to systematically compare the two modalities under controlled conditions, providing insights into how evidence presentation affects truthfulness evaluations. To guide our analysis, we address the following Research Questions:

- **RQ1**: **Effectiveness.** Does the use of summarized evidence achieve comparable accuracy and error metrics to the standard approach of collecting judgments with full-length webpages?
- **RQ2**: **Efficiency.** How does the use of summarized evidence impact the time required for participants to complete truthfulness assessments compared to full-length evidence? To what extent can summarization reduce the costs associated with large-scale truthfulness assessment tasks?
- **RQ3**: **Behavioral Insights.** How does the presentation of evidence influence participants' behavioral patterns, such as reliance on evidence?

The remainder of this paper is structured as follows: Section 2 reviews the background and related work. Section 3 describes our experimental design, including the preparation of data, generation of summarized evidence, the structure of crowdsourcing tasks, and provides demographic statistics. The results are then presented across three key dimensions: effectiveness (Section 4), efficiency (Section 5), and worker behavior (Section 6). Finally, Section 7 discusses the broader implications of our findings, acknowledges the limitations of the study, and suggests directions for future work.

2 Background and Related Work

Multiple studies have explored the application of crowdsourcing for misinformation detection, demonstrating its potential as a scalable alternative to expert fact-checking [26, 37]. La Barbera et al. [25] highlighted the influence of worker bias in assessing statements, an issue further explored by Roitero et al. [42], who observed similar agreement levels across various truthfulness scales. Expanding on this, Soprano et al. [47] and Liu et al. [29] introduced multidimensional truthfulness scales, showing that crowd judgments are reliable across multiple truthfulness dimensions, each capturing different aspects of truthfulness. The comparative performance of crowd workers and experts has also been examined. For example, Zhao and Naaman [54] found that while the crowd performed on par with experts in terms of accuracy, objectivity, and clarity, their assessments often depended on existing professional knowledge. Similarly, Saeed et al. [44] analyzed social network data and demonstrated that crowd evaluations relied on different evidence sources compared to experts, with better scalability and efficiency. Allen et al. [2] further highlighted the scalability of crowd-based methods, noting that political alignment influenced crowd judgments. Additionally, psychological [38] and linguistic [50] peculiarities in misinformation were explored, emphasizing the diverse factors affecting the quality of crowdsourced truthfulness evaluations.

While crowdsourcing holds significant potential, it is not without challenges [14, 22]. Draws et al. [10] identified a general tendency among workers to overestimate truthfulness, often driven by systematic cognitive biases [11, 46]. Bias-aware aggregation methods have been proposed to mitigate these distortions, such as the confirmation bias addressed by Gemalmaz and Yin [19]. Additionally, Nguyen et al. [35] presented FactCatch, a human-in-the-loop system designed to minimize effort while guiding users in fact-checking tasks. Further analyses have explored how biases can be identified and corrected to improve the quality of crowdsourced assessments. For example, Han et al. [20] investigated task

abandonment patterns, while Li et al. [27] proposed methods to enhance labeling reliability by leveraging correlations between labels and neighboring instances. These efforts underscore the importance of addressing cognitive and procedural challenges to maximize the reliability of crowdsourced truthfulness assessments.

Although this study focuses on crowdsourcing, advances in automatic and hybrid fact-checking methods have contributed significantly to the field. Fully automated techniques, including machine learning and deep learning models, have been widely explored for misinformation detection [1, 4, 8, 21, 31]. These methods have been evaluated using public datasets and benchmarks provided by initiatives like CLEF CheckThat! Lab [33, 34] and studies such as Augenstein et al. [5]. Comparative analyses also have been developed to study variability in model performance across datasets [21, 40, 45, 48]. Recent research has also focused on generating human-readable explanations [3, 6, 49, 52] and incorporating complex interactions within machine learning pipelines [28]. Hybrid approaches that integrate human input with machine learning have gained attention as well [9, 39, 51].

In this paper, we leverage automatic signals generated by a state-of-the-art LLM to enhance the efficiency and scalability of a crowd-based approach for truthfulness assessment. By combining LLM-generated summaries with crowdsourced evaluations, we aim to investigate the interplay between automated summarization and human judgment in achieving reliable and cost-effective misinformation detection.

3 Methodology

In this section, we detail the methodology employed in our experiment. To promote transparency and reproducibility, all data collected during the experiment are made publicly available to the research community.²

3.1 Data

This study utilizes the same dataset and adopts a similar experimental design as reported by La Barbera et al. [24], with modifications tailored to meet the specific objectives and requirements of our research. To ensure this paper is self-contained and understandable independently, we report both the details of the data and crowdsourcing task employed. The dataset we use is composed of a subset of statements sourced from the PolitiFact website,³ as also done by previous research [10, 24, 47]. PolitiFact has been an active platform for fact-checking statements from U.S. politicians, political organizations, public figures, and posts on social media since 2007, accumulating over 24,000 fact-checks with regular updates.

PolitiFact statements are categorized by expert judges using a six-level truthfulness scale having levels: pants-on-fire, false, mostly-false, half-true, mostly-true, and true. In our study, we adopt this same six-level scale to maintain consistency and enable direct comparisons between the expert fact-checkers and the crowdsourced assessments. As done in previous work, we select a subset of 120 statements (20 for each ground truth category) from PolitiFact. Additionally, we made sure each was supported by at least 10 webpages retrieved as evidence by using the Bing Web Search API.⁴ These statements form the basis of the crowdsourcing experiments detailed in the subsequent sections.

3.2 Evidence Summarization

We process the evidence related to each statement to create two distinct versions for evaluation: the original, unaltered full-length web page and a more concise summarized version, obtained by leveraging a LLM. To achieve the summarization version, we employ the capabilities of the Meta-Llama-3-8B-Instruct model, a state-of-the-art model known for its robust performance in natural language understanding and generation tasks [12].⁵

The process begins with a carefully crafted prompt that we provide to the model. This prompt is specifically designed to guide the model to extract and summarize the essential factual elements from

²(anonymized link for peer-review) https://osf.io/bnfxm/?view_only=9dcfe098a1ea440b89adbc4574838ff9.

³https://www.politifact.com/

⁴https://www.microsoft.com/en-us/bing/apis/bing-web-search-api

 $^{^5}$ https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct

Table 1: Example of LLM generated summary given the query 'Opposition to having a fully elected Chicago Board of Education is in the "super minority." '.

Evidence

For the first time in Chicago's history, voters would get a say in who runs the city's school board under two competing proposals now before the state Legislature. One calls for a fully elected Board of Education, and the other for a "hybrid" model splitting the school board into some elected members with the majority still appointed by the mayor. [...]

Summarized Evidence

- The document discusses the possibility of having a fully elected Chicago Board of Education, with a focus on the overwhelming support for this idea among Chicagoans, as shown through various polls and referendums.
- The current system of political appointment by the mayor has been in place for 150 years, but there is no consensus among researchers on which form of governance fosters better student performance or fiscal management.
- Over 90% of school districts nationwide have elected boards, and overwhelming majorities of Chicagoans have long favored a switch to an elected board. [...]

System Prompt:

You are a helpful, respectful, and honest assistant. Your job is to provide a summary of the provided documents based on a user query. Your summaries should be as accurate as possible and should not include any harmful, unethical, racist, sexist, toxic, dangerous, or illegal content. Please ensure that your responses are socially unbiased and positive in nature.

User Prompt:

Here is a user query: {statement}. Please do your best to provide a concise list of points which summarize the following document. Please focus on points related to the query. Please output your response as a JSON object with a field "summary" that contains the list of strings. Please first describe what the document is. Then please output five or more strings summarizing the contents of the document. Here is the document: {document content}.

Figure 1: Evidence summarization prompt.

the content of a webpage, ensuring that the generated summary remains the same with respect to the original information in terms of factuality and stance. After several rounds of trial and error, the exact wording of the prompt we use is given in Figure 1. Using this prompt, the model generates a summary that distills the webpage's content into a shorter form, focusing on the most critical information needed to perform the fact-checking task. An example of the summarized evidence is shown in Table 1.

3.3 Crowdsourcing Tasks

We adopt the crowdsourcing task as detailed by La Barbera et al. [24], modifying it to collect questions for our study while preserving the core structure of the original design. This design, originally developed and validated in earlier research [10, 24, 47], allows us to collect truthfulness assessments at scale using crowdsourcing.

We employ a task design featuring sequential data collection, where participants evaluate statements one at a time for truthfulness. We recruit participants through the Prolific platform and apply a filter to include only workers from the U.S. Compensation reflects fair market practices and is based on careful estimations of task completion times, ensuring that payments are both ethical and practical. For the *Standard* modality, we pay each worker £2, while for the *Summary* modality, we set compensation at £1.80. Each worker evaluates a total of 8 statements (one for each ground truth category and two additional gold-standard questions), and 5 distinct workers assess each statement. We recruit 100 workers for each modality, resulting in a total cost of approximately £500, including Prolific's fees.

After filling a demographic questionnaire, the participants perform our task using a structured interface where they first encounter the statement to be assessed, followed by a set of evidences. Each worker sees the title of the web page along with a snippet, similar to the presentation layout of a search engine. Then, depending on the task layout, if the worker clicks on the link they see either the full webpage or its summary. Subsequent to evidence review and selection, participants assess

Table 2: Demographic distribution across modalities.

Consideration	Standard (%)	Summary (%)
Democrat	40	45
Independent	17	23
Republican	40	31
Something Else	3	1
Political Views	Standard (%)	Summary (%)
Conservative	25	23
Liberal	24	26
Moderate	23	25
Very Conservative	11	8
Very Liberal	17	18

the statement. We ask workers to first evaluate the overall truthfulness of the statement using the same six-level scale as the one used by experts. Then, we ask the workers to answer two questions regarding how useful they found the evidence in determining the truthfulness of the statement: "How useful was the evidence?" and "Did you use the evidence to fact-check the statement, or did you have a clear opinion before reviewing the evidence?". For both questions, we collect responses on a five-level Likert scale. The scale for the first question includes the following options: "Not Useful at All", "Slightly Useful", "Moderately Useful", "Very Useful", and "Extremely Useful". The scale for the second question includes: "I did not consider the evidence at all before forming my opinion", "I considered the evidence as much as my initial opinion before forming my final opinion", "I considered the evidence after reviewing it". To ensure high-quality assessments from workers, we implement the following checks: a minimum time requirement of 3 seconds per statement and correct evaluations of two gold-standard questions, one clearly true and the other clearly false.

3.4 Descriptive Statistics

The answers to the demographic questionnaire allow us to assess the demographics of participants across the two experimental conditions. Table 2 presents the distribution of political considerations and views for each condition. The results indicate a balanced representation across both modalities, with comparable percentages for both the political affiliation and ideological orientation. We also measure abandonment [20] to evaluate participant engagement. Initial abandonment (49% for standard, 38% for summary) and mid-task abandonment (10% for standard, 13% for summary) are comparable, with no statistically significant differences observed.

4 RQ1: Effectiveness

4.1 Agreement with Experts

We inspect the agreement between workers and experts, shown in Figure 2. We discuss both the individual and the aggregated scores for both the *Standard* and *Summary* modalities. In terms of individual scores, in the *Standard* modality, we observe an accuracy of 0.31, a MSE of 3.06, and a MAE score of 1.27. The *Summary* modality reports similar accuracy (0.31) but exhibits a slightly higher MSE (3.27) and MAE (1.30). This similarity in the metric scores suggest comparable quality level between the standard and summary modalities, suggesting that the summarized content does not impact workers' effectiveness, which is not trivial as the content presented to the participants in the summary version of the task is substantially condensed. We further examined whether the observed differences in MAE and MSE between the modalities are statistically significant. Using bootstrapped confidence intervals⁶ with 10,000 resamples, we estimated the range of plausible values for the difference

 $^{^6 {\}tt https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.bootstrap.html.}$

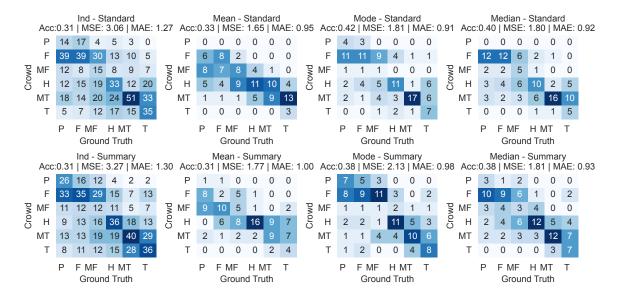


Figure 2: Agreement on individual and aggregated assessments between workers and experts (here and in the following figures we abbreviate the six Politifact levels with their initials).

in these metrics. For MAE, the mean difference was -0.028 with a 95% confidence interval ranging from -0.167 to 0.112. Similarly, for MSE, the mean difference was -0.212 with a 95% confidence interval spanning from -0.767 to 0.340. As both intervals include zero, we conclude that there is no statistically significant difference between the *Standard* and *Summary* modalities in terms of MAE and MSE.

We now turn to aggregated scores, still shown in Figure 2. The scores are aggregated using three distinct statistical methods: mean, mode (i.e., majority voting), and median. The mean offers a general view of central tendency and has proven to lead to higher agreement with expert assessments [24, 47], while the mode identifies the most frequently occurring outcome, and the median provides an additional robust measure of central tendency that is less sensitive to extreme values. In the Standard modality, mean accuracy is slightly higher (0.33) compared to the Summary modality (0.31), though the difference is minimal. Similarly, the Standard modality shows marginally better error metrics, with MSE (1.65 vs. 1.77) and MAE (0.95 vs. 1.00) indicating lower dispersion and deviation from the ground truth. Mode aggregation reflects a similar trend, with accuracy at 0.42 for the Standard modality and 0.38 for the Summary modality, alongside smaller errors (MSE: 1.81 vs. 2.13, MAE: 0.91 vs. 0.98). Median aggregation further supports this finding, with the Standard modality showing slightly better performance across metrics (accuracy: 0.40 vs. 0.38, MSE: 1.80 vs. 2.13, MAE: 0.92 vs. 0.93). While errors in the Summary modality are slightly more pronounced, both approaches achieve comparable accuracy levels. Bootstrap analysis confirms no statistically significant differences across accuracy and error measures. Overall, both modalities show similar effectiveness across several metrics, indicating that, despite the reduced volume of information provided to workers in the Summary modality, it closely resembles the Standard modality in terms of data quality. To test whether worker demographics influence the effectiveness of truthfulness assessments, we additionally run an Ordinary Least Squares (OLS) regression analysis [18]. The results show no statistically significant relationship between demographics and accuracy, indicating that these factors do not substantially impact assessment performance.

4.2 Agreement Among Workers

We employ Krippendorff's α [23] to assess the internal agreement among participants in the two task variations. Krippendorff's α is a robust statistical measure used to determine the consistency of ratings provided by different evaluators, and it is a very popular measure for crowdsourcing tasks [7].

Figure 3 shows the values of internal agreement across the two task modalities, both for the whole task (dotted lines) as well as for the single ground truth levels of the statements. For the *Standard*



Figure 3: Krippendorff's α score.

Table 3: Error types across truthfulness categories.

Modality	Scope	Correct	Over	Under
Standard	Overall	187 (30.6%)	237 (38.8%)	176 (28.8%)
Summary	Overall	185 (30.2%)	232 (37.9%)	$183\ (29.9\%)$
Standard	pants-on-fire	24 (24.0%)	76 (76.0%)	_
	false	39 (37.1%)	44 (41.9%)	35~(21.0%)
	mostly-false	15~(18.3%)	51~(62.2%)	$34\ (19.5\%)$
	half-true	33~(48.5%)	41 (30.1%)	26~(20.6%)
	mostly-true	51 (50.0%)	15~(14.7%)	34 (33.3%)
	true	$35 \ (35.0\%)$	_	65~(65.0%)
Summary	pants-on-fire	26~(26.0%)	74 (74.0%)	_
	false	35 (35.7%)	49~(50.0%)	$16 \ (14.3\%)$
	mostly-false	12~(15.6%)	47~(61.0%)	$41\ (23.4\%)$
	half-true	36 (42.9%)	34~(40.5%)	13~(16.6%)
	mostly-true	40~(50.6%)	28 (32.0%)	$32\ (17.4\%)$
	true	$36 \ (36.0\%)$	_	64~(64.0%)

modality, the α values are generally lower than the Summary modality, reflecting overall less agreement among participants, with the only exception of the pants-on-fire truthfulness level. This suggests that when participants are presented with full-length content, there may be a greater diversity in how the information is interpreted, possibly due to the complexity and volume of the information provided. Furthermore, the lowest α values appear in the categories in the middle of the scale, indicating that the claims with no extreme truthfulness score are also the most challenging for participants to consistently evaluate. Conversely, the Summary modality shows higher α values across all categories except pants-on-fire and for the overall task, which is also statistically significant at the p < 0.05 level according to the Mann-Whitney U Test, indicating a higher degree of consistency among workers ratings. This improvement in internal agreement could be attributed to the condensed nature of the content, which might focus the workers evaluations and reduce both the cognitive load as well as the ambiguity or variability in interpretation that more extensive evidence might introduce. Notably, the alpha values are particularly higher in categories like mostly-false and true where the quality of the summarization may help clarify the key aspects of the statements.

Overall, these findings remark the impact of evidence summarization on the consistency of workers assessments. The higher internal agreement in the *Summary* modality suggests that summarization not only maintains the essential content needed for the truthfulness assessment but may also aid in aligning worker scores, leading to more uniform interpretations and assessments of the veracity of statements.

4.3 Error Analysis

To better understand the patterns of errors in truthfulness assessments, we conducted a failure analysis by categorizing worker assessments into three types: *correct, overestimation*, and *underestimation*. The

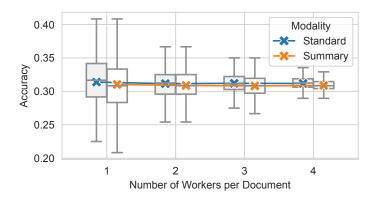


Figure 4: Accuracy across sampling sizes.

results, shown in the first part of Table 3 indicate that the distribution of error types is similar across the two modalities. These comparable distributions suggest that the modality of evidence presentation does not significantly affect the overall patterns of worker errors.

A more fine-grained analysis, shown in the second part of Table 3, highlights the distribution of errors across modalities. In the Standard modality, overestimation emerges as the most frequent error type for categories such as mostly-false (62.2%). Conversely, correct assessments are most common in categories like mostly-true (50.0%) and half-true (48.5%), suggesting workers find it easier to correctly evaluate statements closer to the middle of the truthfulness spectrum. Underestimation occurs less frequently overall but is more pronounced for higher truthfulness categories. In the Summary modality, overestimation remains dominant in the same categories as for the Standard modality. However, correct assessments are slightly more evenly distributed, with the highest rates observed for mostly-true (50.6%) and half-true (42.9%). Overall, these findings suggest that both modalities exhibit similar patterns with respect to error types. We further analyze the mismatch magnitude for overestimation and underestimation errors across the Standard and Summary modalities and find similar error patterns. Both modalities exhibit comparable average mismatch values for overestimation (1.99) and slightly more negative values for underestimation in the Summary modality (-1.73 vs. -1.65). None of these differences are statistically significant, confirming the comparability of the two approaches.

4.4 Robustness to Fewer Judgments

To investigate the robustness of the agreement between worker and expert truthfulness evaluations, we conduct a bootstrap analysis [13]. This method involves resampling the collected assessments with replacement, enabling us to estimate the variability in effectiveness metrics across different sampling sizes. By applying this approach, we aim to understand how the number of workers per document impacts the overall accuracy and consistency of aggregated truthfulness assessments in both task modalities. For each sampling size, ranging from 1 to 4 workers per document (5 would include all workers), we perform 1,000 repetitions during which we compute the individual accuracy of the aggregated assessments compared to expert evaluations.

The results, shown in Figure 4, reveal a trend where the accuracy of both modalities slightly improves (although no statistical significance is observed) with a lower variance as the number of workers per document increases. This pattern is consistent with expectations from crowdsourcing settings, where aggregating multiple assessments tends to mitigate individual biases and errors. Notably, the *Summary* modality achieves effectiveness levels comparable to the *Standard* modality across all sampling sizes. These indicate that summarized evidence can provide comparable results to full-length evidence in terms of both accuracy and consistency, and that this equivalence is achieved while potentially reducing the cognitive load on workers and the resources required for task completion.



Figure 5: Time elapsed on statements for the two modalities.

5 RQ2: Efficiency

5.1 Time

In evaluating the practical aspects of crowdsourced truthfulness assessments, time efficiency emerges as a critical metric, as the more time a worker spends on the task the higher the required cost for its judgment and, as consequence, for the overall task. Figure 5 shows the time required for workers to provide assessments for both task modalities. As shown by inspecting the two series in the plot, the average time taken to complete assessments consistently decreases as the statement index increases (i.e., as a worker performs the task). This trend suggests that participants become more proficient at navigating and processing the tasks over time. Such a learning effect, also observed in previous studies [24, 47], suggests the adaptability of participants and their increasing efficiency in handling the assessments, whether they are dealing with full-length or summarized content.

When comparing the two series we see that the Summary modality consistently shows a reduced average time on each statement index compared to the Standard modality, with the only exception being the second document, and the difference is statistically significant according to the Mann-Whitney U Test [30] at the p < 0.05 level. This supports the observation that time efficiency gained from presenting workers with summarized evidences are real. In practice, the reduced time spent in the Summary modality can lead to enhanced productivity and a lighter cognitive load for participants, which can perform more judgment in the same amount of time and are required to read much less text. Such improvements in efficiency could also translate into cost savings for researchers and practitioners implementing these misinformation assessments at scale, potentially enhancing the economic feasibility of deploying crowdsourced truthfulness evaluations. This can be seen by inspecting the cumulative series in Figure 5, which show the potential for cost savings in large-scale truthfulness assessments. For instance, completing 600 assessments, equivalent to 120 documents, requires approximately 23.67 hours of total work and costing £171.60 at the U.S. minimum wage of \$7.25 per hour (approximately £6.08). In contrast, the Summary modality, reduces the required total work to approximately 20.50 hours, costing £148.63 under the same wage assumption. While these figures are based on the minimum wage, actual costs would scale proportionally if higher wages are offered. When extended to larger datasets requiring (let us say) 6,000 assessments, the Standard modality incurs costs of £1,716, compared to £1,486 for the Summary modality, resulting in higher savings. These findings emphasize the economic advantages of the Summary modality, which maintains comparable performance metrics while significantly reducing worker time and overall costs, making it particularly valuable for large-scale annotation efforts.

5.2 Effectiveness Comparison Under Equal Time Constraints

To evaluate the effectiveness of evidence summarization under equal time constraints, we compared the effectiveness of the two modalities across metrics. Additionally, we assessed the efficiency of each modality in terms of the number of assessments completed within the same time frame, highlighting the potential advantages of summarization for throughput. To ensure a fair comparison, we simulate equal time constraints for both modalities by aligning the total time spent on assessments for each document

Table 4: Comparison under equal time constraints.

Metric	Standard Value	Summary Value
Accuracy	0.312	0.308
MSE	3.063	3.275
MAE	1.270	1.298
Judgment Multiplier	_	+15%

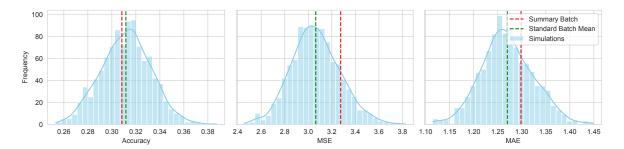


Figure 6: Distributions of Accuracy, Mean Squared Error (MSE), and Mean Absolute Error (MAE) across simulations.

in the dataset. For every document in the *Standard* modality, we compute the total time workers spend on assessments. Then, we iteratively stack assessments from the corresponding *Summary* modality until their cumulative time matches or exceeds the total time recorded for the *Standard* modality. Then, we compute metrics separately for each document in both modalities. We use the *Standard* modality as the baseline and express the relative efficiency of the *Summary* modality as a judgment multiplier, calculated as the ratio of completed assessments in the *Summary* modality to those in the *Standard* modality.

Table 4 presents the comparative results. The *Standard* modality achieves a slightly higher accuracy (0.312) compared to the *Summary* modality (0.308), with minimal differences in error metrics. These findings indicate comparable performance in judgment quality between the two modalities, also considering that no statistical significance is detected. The primary advantage of the *Summary* modality thus lies in its efficiency. On average, workers in the *Summary* setting completed about 15% more assessments than those in the *Standard* setting, offering significant efficiency gains and cost savings, as detailed earlier.

Previously, we used the *Standard* modality as the baseline, stacking judgments in the *Summary* modality to match the total time spent on assessments in the *Standard* batch. In this analysis, we reverse the approach by sampling judgments from the *Standard* modality to match the total time spent in the *Summary* batch, using the *Summary* modality as the baseline. We do that by using a simulation-based analysis. In each of the 1,000 simulations, we randomly sample assessments from the *Standard* modality to match the total time spent in the *Summary* modality. The results are shown in Figure 6. The average effectiveness scores achieved by the *Standard* modality across the simulations indicates that the *Standard* modality maintains a comparable level of accuracy even when constrained by the same amount of time. Also in this case no statistical significance emerges between the two modalities. These findings suggest that both modalities perform similarly in terms of absolute deviations from the ground truth, with no significant disparities in judgment quality.

6 RQ3: Behavioral Insights

6.1 Usefulness and Need for Evidence

In the context of crowdsourced truthfulness assessments, understanding the perceived usefulness of the evidence is important for understanding the quality and trustworthiness of the workers' provided assessments. This provides insight into how the evidence impacts the decision-making process and the reliance of participants on the provided information. Figure 7 shows the perceived usefulness and

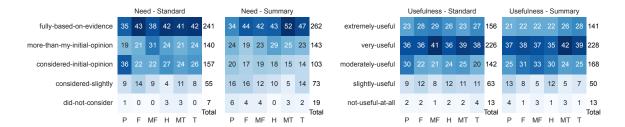


Figure 7: Need and perceived usefulness of the evidence in the task.

necessity of the evidence for the two modalities. We start with inspecting the need for evidence as expressed by participants across different truthfulness levels. Data shows a significant reliance on evidence, with the majority of responses across both standard and summary modalities suggesting that assessments are "fully based on evidence". This strong dependency highlights the critical role that evidence plays in ensuring accurate and reliable assessments. Notably, in the Summary modality, there is a slightly higher tendency for assessments to be fully based on evidence compared to the Standard modality, suggesting that even summarized content sufficiently supports robust judgment formation. Less frequently, participants report that their assessments were "more than my initial opinion" or "considered initial opinion", indicating that while evidence guides their evaluations, preconceived notions or initial impressions also play a role. Interestingly, the number of participants who report their assessments as "considered slightly" or "did not consider" the evidence is minimal, suggesting the minimal influence of unsupported personal bias in the evaluation process.

Turning to the usefulness of evidence, participants across both modalities rate the majority of the evidence as being "extremely useful" or "very useful". This high level of perceived usefulness is consistent across all truthfulness categories, remarking the importance of quality evidence in the assessment task. In the *Summary* modality, there is a notable pattern where evidence is frequently considered at least "moderately useful", which aligns with the reduced amount of information presented to the workers, yet keeping its impact on their assessments. The less frequent ratings of "slightly useful" or "Not useful at all" are significantly lower, which indicates that the evidence provided is overall useful to workers. This is true also for the *Summary* modality, where even summarized information appears to be adequately informative to workers.

Overall, these findings suggest the fundamental role of evidence in shaping the outcomes of crowd-sourced truthfulness assessments. The high reliance on and usefulness of evidence in both standard and summary modalities suggest that effective summarization does not impact the value of the evidence presented to workers.

6.2 Interaction with Evidence

We now detail the result of the inspection of the number of evidences participants interacted with in both the standard and summary modalities during the truthfulness assessment tasks. We focus particularly on the number of evidences clicked by participants for each statement. A specific count of interest was 8, which indicates that participants clicked on exactly one link per statement (including gold questions), suggesting a uniform and minimal engagement across all statements provided in the task. For the Summary modality, we found that out of the total interactions, 511 instances (85.17%) involved clicking exactly eight links to evidence. Similarly, in the Standard modality, there were 520 instances (86.67%) where participants engaged with exactly eight links. This close similarity in percentages between the two modalities indicates a comparable level of engagement when workers are provided with either full or summarized content, in the case of workers that do the minimum amount of work. A similar pattern emerges when we exclude instances where participants clicked on exactly eight links. In such cases, the mean number of links clicked in the Summary modality was 18.70, with a standard deviation of 8.09, whereas in the Standard modality, the mean was slightly lower at 17.50, with a narrower standard deviation of 3.39. This is based on few (approx 15%) of instances, and no statistical significance is measured.

We also extend the analysis to examine the maximum depth of links explored by participants, which reflects how deeply they looked into the provided evidences. We measured the maximum reached depth

Table 5: Correlation values between dimensions.

Modality	Need & Usefulness	Need & Time	Usefulness & Time
Standard	0.483	-0.020	0.030
Summary	0.481	0.004	-0.097

as the ordinal position of the farthest link clicked (e.g., clicking on the fifth link indicates a max depth of 5). It is again the case that the two modalities exhibit a similar behavior. In the *Summary* modality, 85% of participants clicked no further than the first link, similar to 86.67% in the *Standard* modality. When excluding these cases, participants in the *Summary* modality explored slightly more links on average (mean depth 3.63 vs. 3.43, no statistical significance detected), showing comparable engagement across both modalities.

6.3 Interaction Across Evaluation Dimensions

In addition to examining the depth of evidence exploration, we also analyzed the number of times each participant engaged with the assessment dimensions (i.e., truthfulness, usefulness of evidence, and need for evidence). Given that there are three dimensions in our evaluation setup, the minimum number of clicks required is three, one for each dimension. This measure helps us understand the decisiveness of participants and the extent to which they reconsider their assessments during the task.

Our findings show that in the Summary modality, 433 instances (72.17%) involved participants clicking on each dimension only once, thus doing the minimum required number of clicks. Similarly, in the Standard modality, there were 450 instances (75%) where participants also clicked each dimension just once. When we exclude cases where the number of clicks on dimensions is exactly three, we get that for these cases, the Summary modality shows a mean of 4.45 clicks with a standard deviation of 0.67, slightly less than the Standard modality, which shows a mean of 4.60 clicks and a standard deviation of 0.99. No statistical significance is detected. These statistics suggest that participants in both modalities generally stick to their initial assessments. The similar levels of engagement suggest that summarized content appears to be sufficient for making assessments. The slightly lower variance in the number of clicks in the Summary modality further reinforces this point, suggesting that participants are slightly more consistently confident in their assessments.

To further explore the interplay between key dimensions in the assessment process, we conduct a correlation analysis examining the relationships among need, usefulness, and time elapsed for both modalities (Table 5). The results reveal a consistent moderate positive correlation ($\rho \approx 0.48$) between need and usefulness, indicating that participants who perceive the evidence as more necessary also tend to consider it more useful, irrespective of whether they are presented with full-length or summarized content. This relationship underscores the complementary nature of these two dimensions, as both contribute to the assessment process. However, the moderate strength of the correlation suggests that while need and usefulness are related, they are not interchangeable. Instead, these dimensions capture distinct aspects of participants' interactions with evidence. On the other hand, the correlations between need and time elapsed, as well as usefulness and time elapsed, are negligible or weak ($\rho \approx -0.02$ to -0.09), showing limited influence of these perceptions on task duration.

In order to more deeply analyze interactions between the three assessment dimensions measured for the two modalities (i.e., time elapsed, need, and usefulness), we performed an OLS regression analysis, augmented by ω^2 effect sizes [36], which is well-established in the literature for quantifying effect sizes [15–17, 41, 53]. The results confirm that the Summary modality significantly reduces task time when compared to the Standard modality (p < 0.05, $\omega^2 = 0.0036$). Conversely, perceptions of need, usefulness, and their interaction exhibited no statistically significant effects on task duration, with negligible ω^2 values (-0.0008 for need, -0.0001 for usefulness, and -0.0005 for their interaction).

7 Conclusions and Future Work

This study investigates the potential of summarized evidence to enhance the efficiency, effectiveness, and cost-effectiveness of crowdsourced truthfulness assessments. For **RQ1** (Effectiveness), our results suggest that the *Summary* modality achieves accuracy and error metrics comparable to the *Standard*

modality. While slight differences are observed in MSE and MAE, these are minimal and do not affect the practical utility of the *Summary* approach. These findings affirm that summarization effectively preserves the critical information necessary for accurate truthfulness assessments.

Regarding **RQ2** (Efficiency), we find that the Summary modality substantially reduces the time required for participants to complete their assessments compared to the Standard one. Workers using summarized evidence complete nearly double the number of judgments within the same time frame. This efficiency gain highlights the potential of summarization to enhance throughput in large-scale truthfulness assessment tasks, particularly in time-sensitive scenarios. Addressing cost-effectiveness, we find that summarization significantly reduces the costs associated with large-scale truthfulness assessments. By enabling workers to complete more judgments within the same time frame, the Summary modality reduces overall task costs without sacrificing quality. This economic advantage is particularly relevant for scaling fact-checking efforts where budget constraints are a key consideration.

In terms of **RQ3** (Behavioral Insights), we observe that the *Summary* modality does not diminish participants' reliance on or perceived usefulness of evidence. Furthermore, the *Summary* modality produces higher internal agreement among workers, suggesting that the condensed presentation of information aligns participant judgments more effectively. This indicates that summarization not only maintains but also enhances certain aspects of the decision-making process, supporting consistent and evidence-based assessments.

Despite these contributions, certain limitations must be acknowledged. First, the reliance on automatically generated summaries introduces the possibility of omitting critical nuances present in full-length evidence, which may impact worker judgment in complex cases. Additionally, our study focuses on a specific dataset and task context, which may limit the generalizability of our findings to other domains or settings. Finally, while the *Summary* modality demonstrates promising efficiency, further research is needed to explore its long-term effects on worker fatigue, engagement, and the potential biases introduced by condensed evidence.

While these findings highlight the promise of summarization, they also leave analysis open for future exploration. One direction is to refine summarization techniques to better tailor evidence to specific truthfulness categories or individual worker preferences, which could further improve accuracy and efficiency. Another area of investigation is the impact of evidence presentation on worker satisfaction and engagement, which could offer insights into designing more intuitive and rewarding tasks. Additionally, applying these methods to other domains, such as health misinformation or scientific claims, would test their applicability and effectiveness in different contexts. Another promising direction for future work is the exploration of multi-document summarization techniques. By consolidating multiple pieces of evidence into a single, coherent summary, this approach could potentially improve worker accuracy and reduce cognitive load, especially when participants prefer to engage with a single document.

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