Enhancing Corporate Communication with AI-summarized Disclosures

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August 2025

ABSTRACT

We conduct a field experiment where we provide investors with AI-generated summaries of annual reports during virtual conference calls. We find that providing annual report summaries increases both the quantity and quality of investor engagement during the calls. Treatment firms experience a 46% increase in the number of investor questions, relative to control firms. Investors' questions for treatment firms are (i) longer, (ii) contain more numerical content, and (iii) address issues requiring higher-level cognitive processing. Questions are more likely to address topics covered in the summaries, particularly when investors are less experienced or when the annual reports are longer and contain negative sentiment. Additionally, management's responses during calls of treatment firms become longer and more detailed. The capital markets also react more strongly to these calls. The findings suggest that AI-generated summaries can help investors process annual reports' content by highlighting key information and enhancing the reports' saliency.

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JEL classification: G00, M40, M41.

Keywords: Retail investors, Generative AI, LLMs, information processing costs, field experiment, virtual conference calls.

Acknowledgements: We are grateful for helpful feedback from Joachim Gassen (*discussant*), Steph Grant (*discussant*) and workshop participants at 2025 ABFER Conference, BYU, 2025 CAPANA Conference, George Washington University, Harvard Business School, Penn State Accounting Conference, Shanghai University of Finance and Economics, USC, the University of Michigan Centennial Conference, and the Hosmer Interdisciplinary Research Lunch. We thank Fei Jiang, Jinxing Hao, and Wenqin Yu for excellent research assistance. Yu acknowledges financial support from the Ross School of Business.

1. INTRODUCTION

An important goal of corporate communication is to increase the engagement level of investors. Studies show that investor engagement can reduce information asymmetry and build investor confidence (Bushee and Miller [2012]), but it can also raise concerns. Investors vary widely in their sophistication levels, and their broader participation may disrupt management's control over the disclosure narrative (Choi, Huang, Qiu, and Zhang [2024]). These risks are amplified as corporate reports become more complex, imposing greater processing demands on less sophisticated investors. In this paper, we examine whether providing summaries of annual reports can enhance investor engagement, which in turn could help investors process the annual report's content.

Providing summaries could increase investor engagement by serving as a focal point for communications with management. Summaries enhance the saliency of the annual report content by making key information more prominent. Investors may perceive the summary information as more important and exert more effort into processing its content (Cheng, Roulstone, and Van Buskirk [2021]; Elliott, Grant, and Hobson [2020]).[1] Investors' questions based on a summary may thus be more informed and lead to deeper discussions of more relevant topics.

[1] The idea that summary reports will help reduce information-processing costs, especially for less sophisticated investors, has been the primary motive for the SEC's proposal of the "two-tiered" financial reporting system (SEC 1995)—an earlier regulation that considered requiring firms to disclose summary reports of the 10-Ks. We discuss this reporting system and its implications in Section 2.

However, summaries condense information contained in the full report, some of which may be important. If investors rely solely on the summarized content without considering the full report, it may limit investors from consuming the complete information set. Consequently, summaries may lead investors to ignore relevant information from the report (Hirshleifer and Teoh [2003]).

A challenge in examining the role of summaries in archival settings is that the timing and methods employed to produce summaries vary across firms and may correlate with other underlying economic factors that will impact investor engagement. Furthermore, summaries of corporate disclosure are often produced by managers, who may introduce bias by selectively highlighting only favorable news (Cardinaels, Hollander, and White [2019]). To overcome these challenges, we provide AI-generated summaries of firms' annual reports, created by computer algorithms that have no incentives to favor the firm. We generate the summaries for a random set of treatment firms and examine whether disclosing the summaries changes investor participation and the nature of the questions they raise. Our experimental setting alleviates the concern of the selection effect from firms that choose to provide summaries.

We conduct our experiment in China using the annual report briefing meetings known as earnings communication conferences (ECCs). Starting in 2004, all listed companies on China's main stock exchange were directed to hold an ECC within 15 trading days of their annual report release. One advantage of the ECC setting is that the calls are open to the public and held almost exclusively online.[2] The virtual setting allows us to include a broader audience range, as participants can join from anywhere by simply clicking on the platform. Another important feature of the ECC setting is that any participant can ask questions using the open chat feature. This contrasts with earnings conference calls in the U.S., where participants cannot ask a question unless they are called on by management.[3] The setting allows us to collect the complete set of questions raised by all investors and the corresponding answers. The observability of the complete set of questions and the subsequent dialogue allows us to understand how providing summaries affects communication between management and investors.

We focus on annual reports for several reasons. Prior studies find that investors face significant information overload from annual reports, which have become increasingly lengthy over time (Bonsall, Leone, Miller, and Rennekamp [2017]; Dyer, Lang, and Stice-Lawrence [2017]).[4] The reports' bloated content may not always contain new information and imposes significant processing costs on investors (Dyer, Lang, Stice-Lawrence [2017]; Kim, Muhn, and Nikolaev [2024]). We rely on prior studies that find generative AI technology can be helpful in reducing annual reports' complexity (Cardinaels et al. [2019]).[5]

[2] While the regulation does not stipulate the format of the conference calls (it only requires firms to host calls in a format easily accessible to investors), virtual calls have become widely popular since the onset of COVID-19. As of 2024, more than 90% of companies on the main exchanges host their ECCs using an online platform, according to statistics released by the China Listed Companies Association (CLCA).

[3] Studies find that management discretion can lead to selective participation and skew the questions towards more sophisticated investors, such as security analysts and institutional investors (Mayew, 2008; Brown, Call, Clement, and Sharp, 2015).

[4] The average length of annual reports in China is approximately 200 pages, which is comparable to the average length for U.S. firms.

[5] Cardinaels et al. [2019] examine the role of summaries using the earnings release of a single hypothetical retail company, recruiting participants from MTurk to assess the impact of summaries on individuals' judgments. In contrast, we use summaries of actual annual reports from a broad cross-section of firms. Also, we evaluate investor engagement based on the investors' participation and management's responses.

Following this literature, we use generative AI to populate summaries of five key topics in the company's annual report. We select five as the number of topics based on studies showing that the cognitive overload of human working memory starts after processing 7(+/-2) units of information (Atkinson and Shiffrin [1968]). We present these summaries to investors in a bullet point format.

Our sample includes all firms that hosted virtual calls on the Quanjing platform (also known as P5W Net) in 2023. Quanjing is the largest conference call platform in China and hosts conference calls for more than 47% (1,301 out of 2,771) of the firms listed on the Shenzhen Stock Exchange.[6] Our sample includes 1,105 firms that are listed on the main board of the three major stock exchanges—Shenzhen (SZSE), Beijing, and Shanghai—and held an ECC on Quanjing's platform in 2023.

For treatment firms, we inserted an "Annual Report Highlights (ARH)" icon on each firm's 2023 ECC announcement page. The ARH icon was linked to the annual report summary, which was produced by the researchers using AI technology [see Figure 1]. The icon was visible during the ECC presentations. When investors clicked on the link, they were presented with a pop-up window with a five-point summary of the annual reports on their screens [see Figure 2, Panel A].[7] This was our baseline treatment. We added an additional treatment where each of the five points was classified by its sentiment: positive, negative, or neutral [Figure 2, Panel

[6] Quanjing was owned by the Shenzhen Stock Exchange before People's Daily acquired it. It hosts the largest number of conference calls in China, primarily covering firms listed in Shenzhen. Other platforms, such as China Securities and SEE, are smaller but focus on firms listed on the Beijing and Shanghai exchanges.
[7] The average number of clicks on each link was 23 (range: 0 to 200), which was 10% of the average number of participants on the calls.

B]. The second treatment was designed to reduce investors' information-processing cost of interpreting the sentiment of the summarized topic.

We find that including summaries of annual reports leads to a significant increase in investor engagement. Treatment firms receive significantly more investor questions: 19.86, compared to 14.27 for the control firms. The summaries do not necessarily lead to more investors attending the calls, but do seem to increase engagement of those in attendance.

While the increase in the number of questions is promising, it does not necessarily indicate improved engagement, especially if the questions raised are superficial or off-topic. [8] We analyze the content of the investor questions to examine the quality of the questions. We find that questions of treatment firms are 11.7% longer and are 4% more likely to contain numerical evidence (from 36% to 40%). We also delve into the nature of the questions and test whether questions are reflective of higher cognitive thoughts. We use Bloom's taxonomy of cognitive complexity (Anderson & Krathwohl, 2001) and classify questions into lower-level cognitive processing (e.g., *Understanding*) to higher-level processing (e.g., *Evaluating*). Investors of treatment firms are less likely to raise questions about understanding the report content than those of control firms (19.72% vs. 26.25%). Treatment firms face more questions about evaluating the content of the report (58.21% vs. 52.64%). For treatment firms, we find an overall shift in the nature of questions raised by investors that represent higher cognitive

[8] Off-topic questions can disrupt the flow of the call or take up time that could otherwise be used on more meaningful questions. It is possible that our summaries make participants ask more off-topic questions because they want to differentiate themselves from others by broaching issues not already raised. The fact that all questions are publicly visible on the platform could make investors more susceptible to such an audience effect (Triplett [1898]; Zajonc [1965]).

processing. Taken together, the finding suggests that summaries motivate investors to exert more effort in producing higher-quality questions (Elliott, Grant, and Hobson [2020]).

We also find that the question topics are more likely to align with the topics presented in the summary (*Alignment*), suggesting that investors actively use the summary content to develop their questions. Relative to control firms, the questions asked of treatment firms are 7% more likely (50% vs. 57%) to align with topics from the summary. In cross-sectional tests, we find that investors rely more on the summaries (i.e., their questions have higher *Alignment*) when the annual reports impose greater processing costs: when the annual reports are longer with negative sentiment (Dyer et al. [2017], Loughran and McDonald [2011]).

We next examine investor characteristics to test which type of investors are more likely to use the summaries. Due to the anonymous nature of ECCs, we do not have the identities of the investors who post questions. We instead consider their track record on the platform using their anonymized IDs.[9] Specifically, we measure their experience level based on how active they were on the platform in the prior year. We find that silent investors—those who did not ask any questions in 2022—are more likely to ask questions that are guided by the summaries. Vocal investors—those who asked questions in 2022—pose slightly more questions than before, but are less likely than silent investors to ask questions guided by the summaries. Interestingly, these vocal, experienced investors shift to topics not raised in the summary. These findings suggest that the summaries are more likely to guide investors with less experience, who are

[9] When participants register on the Quanjing platform, they are asked to authenticate their identities by providing their citizen number or phone number. Due to security reasons and IRB requirements, we were provided with the registrants' anonymized registered IDs (if available) but not their phone numbers.

more likely to suffer from the high cost of processing annual reports. The concurrent, albeit modest, increase in the number of questions asked by experienced investors indicates that more participation by the inexperienced does not necessarily displace participation by the experienced.

We find changes in the properties of the management responses. We find that the treatment firms' answers are 11.4% longer than the control firms. Treatment firms' answers more directly address the investors' questions and provide more specifics, with more numerical data and supporting evidence. We also test whether the responses differ between aligned and non-aligned questions. We find a significant improvement in response quality for all questions, regardless of alignment. The improvement for both question types, aligned and non-aligned, indicates an overall enhancement in the information content of the conference call.

Finally, we examine how increased investor engagement affects the information efficiency of capital markets (Grossman and Stiglitz [1980]; Blankespoor et al. [2020]). We expect enhanced engagement to increase investors' use of the annual report, leading investors to depend more on the information, and thereby increase their reaction to these announcements. Consistent with this, we find that the capital market reacts more strongly to calls for treatment firms. Treatment firms experience higher trading volume. We also find a stronger market reaction to the information release event, but only within the subsample of treatment firms that experience greater engagement during the call. We interpret these results as summaries leading to increased investor engagement and more active consumption of the annual reports.

Our paper contributes to the following literature. First, we add to the literature on investors' information-processing costs. For researchers, it is challenging to identify events that represent an exogenous change in information-processing costs. Regulations that are designed to ease the processing burden typically lack a plausible benchmark due to market-wide implementation (Blankespoor [2019]; Goldstein, Yang, and Zuo [2023]). Other studies rely on indirect measures that capture changes in the opportunity cost of processing information (Hirshleifer, Lim, and Teoh [2009], deHaan, Madsen, and Piotroski [2017]; Darendeli [2024]). Our experimental setting allows us to provide causal evidence on how providing summaries lowers the processing cost of investors.

Second, our findings contribute to the research on individual investors and their increasing use of technology. The rise of information technology has helped individual investors to emerge as a collective group that can meaningfully impact the capital market (Wong, Yu, Zhang, and Zhang [2024], Brochet, Chychyla, and Ferri [2023]). However, studies find mixed evidence on the efficacy of retail investors' participation (Croom, Grant, and Seto [2023]; Markov and Yezegel [2023]; Choi, Huang, Qiu, and Zheng [2024]; Gao and Huang [2020]). Individuals may not possess the necessary skills to process information, and their presence may lead to heightened market volatility (Barber and Odean [2008]). In this paper, we show how AI tools can be used to inform individual investors, especially among those who face a higher burden to process complex corporate disclosures. We find that AI summaries have a greater impact on less sophisticated users of corporate disclosure, especially in times when the disclosed information is more complex (Rennekamp, Zuckerman, and Lev [2021]).

Third, our paper contributes to the literature on conference calls and interactions between management and investors. Some prior studies attempt to infer the participants' engagement levels from the participants' attributes (Mayew, Sethuraman, and Venkatachalam [2020]). Others use the conversation itself as the unit of analysis to gauge market participants' engagement levels (Rennekamp, Sethuraman, and Steenhoven [2019]). We build on this line of literature and show that the extent to which investors engage with topics relevant to the existing disclosures can affect their overall engagement level.

2. INSTITUTIONAL SETTING

2.1. Annual reports and the role of summary

Annual reports have become increasingly lengthy and complex, which can create cognitive overload for investors. Providing summary reports to investors may help them better extract key insights from annual reports and attend to information they might otherwise neglect due to processing costs (Hirshleifer and Teoh [2003]). In hopes of helping investors (particularly less sophisticated ones) process their annual reports' content, firms have thus begun providing various forms of summaries along with their annual reports.[10]

In the 1990s, the SEC considered requiring firms to disclose summary reports with their 10K releases.[11] However, the Commission eventually discarded this proposal after significant

[10] Prior studies find that the informativeness of summaries varies based on their presentation format (Maines and McDaniel [2000]) and linguistic properties (Davis, Piger, and Sedor 2011).

[11] In 1995, SEC proposed a "two-tiered" financial reporting system (SEC 1995), which involved producing a reduced-form annual report by abbreviating (or recasting) the complete financial statements. Bushman et al. (1996) show that providing a summary report can lead to improved liquidity of firms, even when there is less private information gathering by those less likely to rely on the summary report.

pushback from the capital market. Two concerns that were raised at the time about summary reports may still apply today. The first concern is that the information-reduction process may eliminate important content from the full report. If it does, and if less sophisticated investors fixate on the summary report, then providing them with a summary might limit their information set.[12] The second, and perhaps more significant, concern is that a summary may provide a biased view of a firm due to managerial opportunism. If firms are free to choose the key insights from their own reports, managers may select ones that are favorable to the firm.[13]

A key feature of our study is that the summary reports are not produced by firms. Instead, we use computer algorithms aided by AI technology, which have no clear incentive to select information favorable to the firm. However, other aspects of AI technology may add noise to the summary (e.g., hallucination). We therefore test the quality of the AI-generated summaries and find that they are of higher quality than human-generated ones. Another appealing feature of the AI technology is that it is readily available to all investors at very little cost, making the study's findings easily implementable even for less sophisticated investors.[14]

2.2. Earning Communication Calls (ECCs)

Although the release of annual reports is one of the most anticipated disclosure events for Chinese firms (Bian et al. [2021]), prior studies suggest that the reports often result in

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[12] Bushman et al. [1996] show that the two-tiered system can be detrimental to unsophisticated investors when the summary report eliminates important value-relevant information. However, the liquidity effect of providing a summary report will always be positive, even when the summary results in less private information-gathering by sophisticated investors.

[13] Some studies show that summaries prepared by managers are shaped by strategic incentives to highlight favorable news. Cardinaels et al. [2019] find that manager-generated summaries contain a more opportunistic tone and content than summaries provided by computer algorithms.

[14] Following our experiment, based on requests from many firms, the platform started to provide the summary service to *all* firms that host ECCs on it.

significant information overload for investors. The reports are sometimes bloated with minimally informative text, which may add to the information asymmetry among investors (Kim et al. [2024]). The problem is particularly acute for individual investors, as they may lack the skills to process public information and may not have access to private communication channels.[15]

To help all investors, the China Securities Regulatory Commission (CSRC) advises that all public firms host a conference call within 15 trading days of their annual report's release. While this is not an explicit regulatory requirement, the majority of listed firms do host ECCs within that timeframe. The high adoption rate reflects the quasi-mandatory nature of the soft law system in China (Cheng, Hail, and Yu [2022]).[16,17] One trend since COVID-19 is that these conference calls are increasingly held online. According to the latest records from the CLCA, 90% of ECCs were conducted virtually in 2022.

In 2005, the Quanjing platform, ultimately controlled by the Peoples' Daily, became the first online platform to host virtual ECCs. The platform was set up in response to a Shenzhen Stock Exchange regulation, included in its 2004 "Guidelines for the Protection of Investors' Rights and Interests on the SME Board," requiring that companies listed on the SME board host ECCs after publishing their annual financial reports. At that time, all ECCs were organized

[15] Individual investors account for approximately 85% of the trading in China's stock exchanges (Wong et al. [2024]).

[16] The latest statistics from the China Listed Companies Association (CLCA) indicate that 5,130 companies from the Beijing, Shanghai, and Shenzhen stock markets (96.10% of all listed firms across the three exchanges) held conference calls for their 2024 annual reports.

[17] Our conversation with numerous board secretaries confirms that while the rules are not explicit, most firms view conference calls as mandatory in practice.

by and held on the Quanjing platform. Since then, other conference call platforms, such as China Securities and SEE, have been established by the Beijing and Shanghai Stock Exchanges. However, Quainjing continues to be the largest, hosting about one-fourth of all conference calls in China in 2024.

The annual report conference calls are open to current and prospective investors of the hosting firms. Each participant must register on the conference call platform using their resident ID number or phone number. Given that financial analysts and institutional investors can engage with management through many direct communication methods (e.g., site visits and phone conversations), retail investors constitute the predominant demographic of conference call attendees (Bian et al. [2021]). The China Securities Regulatory Commission (CSRC) reports that retail investors make up a large portion of the participants attending ECC calls.[18]

2.3. Mechanics of Earnings Communication Calls

China's annual report conference calls are similar to U.S. earnings calls in that investor can ask questions about firms' annual earnings and their outlook. A growing portion of firms in China hold their conference calls virtually. Unlike in the U.S., where the format of virtual conference calls varies widely (e.g., hybrid or virtual-only), the ECCs' format is uniform, with all calls being virtual-only and no in-person option. A typical ECC includes a presentation

[18] The records indicate that more than 700,000 individual investors participated in ECCs in 2022.

followed by a Q&A. The presentation can be a pre-recorded promotional video or a PowerPoint slide presentation delivered in real time.

The Q&A session of ECCs is conducted using a chat function. Participants can submit questions at any time during the Q&A (and sometimes before the meeting), and can designate who should respond (e.g., CEO, CFO). The management team is strongly encouraged to answer all questions.[19,20] Both the answer and the question become visible to the public at the time the firm posts its response.

Another unique feature of ECCs is that participants can freely submit questions. This feature is distinct from conference calls in the U.S., where participants must be called on by the manager before they can ask a question. U.S. conference calls are predominantly attended by financial analysts and institutional investors, whose names are made known to the firms during the calls. These participants often have incentives to maintain access to management and may therefore be reluctant to ask confrontational questions. In contrast, ECC participants are predominantly individual investors who have no incentives to maintain access, and they are protected by anonymity. Thus, it is possible that their questions challenge management more directly than the questions during U.S. conference calls.

3. SAMPLE AND EXPERIMENT DESIGN

[19] Firms are allowed to withhold inappropriate questions (i.e., those involving foul language or personal attacks) and redundant questions.

[20] Consistent with Bian et al. [2021], we find that firms withhold, on average, 13% of all submitted questions, which suggests that they answer most of the investors' questions.

3.1 Sample Selection

Our experiment was conducted on firms that hosted their 2023 annual report conference calls on the Quanjing platform. We start with an initial sample of 1,168 listed firms that hosted ECCs on their prior-year (in 2022) annual reports on the platform. A majority of our sample firms are listed on the SZSE, where Quanjing has its market dominance.[21]

During the 2023 conference call season, some firms from the initial sample discontinued their use of the Quanjing platform, while other firms hosted their first calls on the platform. We randomly assign the newly participating firms to the control or treatment group once their conference call dates are confirmed (typically seven days prior to the call). Our final analysis includes a sample of 1,105 firms, of which 815 (73.49%) are from the initial sample and 290 are new additions.

Prior to the experiment, we randomly assign firms to either the control group or one of two treatment groups. Specifically, 30% of the firms are allocated to the control group, while the remaining 70% are evenly split between the two treatment groups: *Summary* (35%) and *Summary & Sentiment Label* (35%). Details on these treatment conditions are in Section 3.2.1.

Table 1, Panel A presents the distribution of firms across the treatment and control groups. We have 1,105 sample firms, consisting of 762 treatment firms and 343 control firms. Panel B presents the covariate balance between the treatment and control groups. The financial data and analysts following data for 2023 are collected from CSMAR. We report the means for variables

[21] Our sample covers approximately 40% of all firms listed on the SZSE. In untabulated results, we perform a balance test comparing the Quanjing sample firms with the entire population of SZSE-listed firms. Firms using the Quanjing platform are slightly smaller and more profitable than the average SZSE-listed firm, but in other characteristics the two groups are largely comparable.

such as the log of total assets at year-end (*Size*), return on assets (*ROA*), a binary variable indicating whether the firm is state-controlled (*SOE*), the percentage of shares held by institutional investors (*Institutional Holdings*), the number of analysts covering the firm (*Analysts Following*), and earnings surprise (*Earnings Surprise*). The descriptive statistics show that compared to the U.S. conference call firm sample, our sample firms have less institutional holdings (37%) and fewer analysts following (5.33), on average. The balance tests show that the observable covariates are well-balanced across the treatment and control groups, with no significant differences in these characteristics.

3.2 Experimental Design

Our experiment was conducted from April 7 to May 31, 2024. Our intervention involved posting summaries of annual reports on the conference call platform. Quanjing provided us with the conference call schedules once the meeting dates with the firms had been confirmed. Since all listed firms are required to hold their annual conference calls within 15 days *following* the publication of their annual reports, we had time to create the five summary points of each firm's annual report prior to the meeting[22].

We use Kimi AI, an OpenAI Generative Pre-trained Transformer (GPT) alternative in China, to identify the five key summary points from each firm's 2023 annual report.[23] GPT is widely and effectively utilized in areas that deal with text, including text summarization. Kimi

[22] The prompt for all firms was the following: "Please summarize five key points around the fundamentals based only on this annual report, and elaborate on each point in detail."

[23] We also considered having fewer than or more than five summary points. We chose to use five in order to strike a balance between providing enough information and not overloading investors, as discussed in prior research (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10322198/#).

AI is one of the most widely used AI chatbots in China, according to the latest report from the World Bank (Liu and Wang [2024]). It is known for its ability to process long text and is equipped to manage Chinese documents efficiently and directly.[24]

Our experiment includes the following two treatment groups.

Summary **(35%)**: For this group, a summary consisting only of the five key points was posted on each company's page in the annual conference call section.

Summary & Sentiment Label **(35%)**: Summaries were also posted for this group, but each key point was accompanied by a sentiment label: positive, negative, or neutral.[25] We manually assigned the label to each summary point.[26] We introduced the second treatment group—and included the sentiment labels for each of the five summary points—to reduce investors' uncertainty about whether each key point represented good or bad news for the firm. See Appendix A1 for an example summary for each treatment group.

For the control group, which makes up 30% of the sample, no intervention was applied. That is, a summary for the annual report was generated for each firm (to establish a baseline for the empirical tests), but was not posted on the platform.

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[24] In untabulated tests, we assess the quality of AI-generated summaries by comparing them to human-generated summaries. We randomly sample 90 reports—60 from the two treatment groups and 30 from the control group—representing approximately 8% of our sample. We recruit 12 accounting majors at Southwest University of Finance and Economics to generate five key-point summaries of the annual reports, instructing them to (1) maintain a length similar to the AI-generated summaries and (2) use terms from the annual report rather than their own wording. We have two students summarize each annual report to mitigate the effect of individual errors. We evaluate the quality of AI-generated summaries using BERTScore, an evaluation metric that leverages contextual embeddings from the BERT model. The results show that AI-generated text achieves higher scores than human summaries (0.65 vs. 0.61), with the difference being statistically significant.

[25] In the experiment, we use the term "Future Growth" as the label for positive sentiment, "Steady Development" for neutral sentiment, and "Potential Risks" for negative sentiment. We avoided directly using "positive," "neutral," and "negative" because the treatment firms might have objected to such direct labeling.

[26] This was carried out by three accounting students at Southwest University of Finance and Economics.

3.2.1 Posting Summaries of Annual Reports on the Conference Call Platform

For the two treatment groups, we posted, on the page announcing each firm's annual conference call, a link titled "Annual Report Highlights (ARH)." Investors could access the summary points by clicking the link, which was available from the time when the upcoming conference call was announced on the platform (typically seven days before the call) until the conclusion of the call.

We began the experiment on April 7, 2024,[27] the first day after a public holiday for a Chinese festival, with two conference calls initiated on the Quanjing platform: Shandong Chenming Paper (SZSE code: 000488) from the treatment group and Suzhou Sushi Testing Group (SZSE code: 300416) from the control group. The experiment concluded on May 31, 2024, the day by which all listed firms were expected to have held their annual conference call.

3.2.2 Outcomes

We collect all questions and answers exchanged on the platform between the hosting firms and participants. Quainjing directly provided us with data on the participants' IDs (anonymized).

We consider three sets of outcomes. First, we assess overall participation in the conference calls by measuring (1) the number of participants, and (2) the total number of questions raised during the Q&As. These metrics were provided directly to us from Quanjing's records. Quanjing recorded every participant question (20,031 in total), including the small portion

[27] This was not the first day of the conference call season. Approximately 90 listed firms hosted conference calls over a three-month period prior to this date.

withheld by management (2,614). For our main analysis, we focus on the total number of questions, regardless of whether they were withheld.[28]

Next, we analyze the content of investors' inquiries to determine whether posting the summaries on the conference call webpage leads to longer, more analytical questions that reflect higher cognitive processing. We also examine whether investor questions align with the topics in the summary. We examine alignment based on the likelihood that the question topic (e.g., disclosure) matches the topics in the summary. Lastly, we assess whether posting the summaries improves the quality of firms' responses.

4. EMPIRICAL TESTS AND FINDINGS

4.1 Descriptive Statistics of the Annual Report Summary

For each company, we generate summaries that list key points of the firms' 2023 annual report. We train Kimi AI to classify each of these points into one of 15 predefined topics: 1. Financial Information; 2. Production Management; 3. Product Market; 4. Supply Chain; 5. Innovation; 6. Risks; 7. Government Policy; 8. ESG; 9. Financing; 10. Strategy; 11. Payout; 12. Business Cooperation; 13. Investors' Relationship; 14. Capital Market; 15. Others.

The 15 categories are populated using the following process. We begin by manually reviewing 300 randomly selected key points, consolidating them into 15 distinct topics, and

[28] All questions must be published and addressed by the management team, except those that are abusive, involve personal attacks, or are deemed redundant. The exchange strongly encourages listed companies to actively respond to investors' questions during the conference call, allocate sufficient time for Q&A, and ensure both a high response rate and high-quality replies. Our findings remain qualitatively unchanged when we exclude questions that were withheld and not addressed by the firms.

assigning appropriate labels. We present Kimi with 250 of these labelled observations (setting aside the remaining 50 for out-of-sample testing) and direct it to categorize each topic into one of the 15 topics, adhering to the classification logic we had established.[29] We repeat this process using 300 investor inquiries to classify the topic of each investor question.

Table 2, Panel A presents the distributions of topics of the key points in our sample. Overall, we find that the topic distribution is comparable between the control group and the treatment group. *Financial information* has the highest likelihood of being a key point in the annual reports, with a prevalence of 26.27%. This is consistent with our expectation that financial details are critical in annual reports because annual reports are designed to communicate firm performance. Next in significance are *Innovation* and *Risks*, which account for approximately 17.45% and 13.91%**,** respectively, of the key points across our treatment and control groups. These topics provide investors with insights into a company's environment, prospective growth opportunities, and potential risks.

We also manually assign a sentiment label (positive, neutral, or negative) to each summary point.[30] Table 2, Panel B, presents the distribution of the three sentiment types for the key summary points. Approximately 70% of the key points in the annual report summaries are presented with a positive tone, and 11% with a negative tone. The distribution reflects firms' tendency to present a favorable outlook and downplay adverse news in their annual reports. We

[29] Our detailed prompt is: "We have a total of 15 categories as follows, and based on these categories, we have provided a set of annotated samples for you to read first. To which category does XXX most directly belong?" The out-of-sample accuracy of the classification is 92%.

[30] This was carried out by three accounting students at Southwest University of Finance and Economics.

find no significant difference between the control and treatment groups in sentiment distribution, further confirming that the randomization process produces balanced samples.

4.2 Investor Engagement

To examine whether posting a five-point summary of the annual report encourages investor engagement during the calls, we estimate the following firm-level regression equation:

$$\text{Engagement}(Questions_i\ /Participants_i) = \alpha + \beta_1\ T_i + \sum \beta_n\ Controls_i + \text{FE} + \varepsilon_i \qquad (1)$$

where the outcome variable, $Questions_i$, represents the total number of questions submitted by participants through the online platform during the conference call for firm i. $Participants_i$ serves as another metric of investor engagement: it is the total headcount of individuals who joined the conference call for firm i. T_i represents our treatment group assignment, with *Treat* indicating that firm *i* was assigned to *either* treatment group and *Summary* and *Summary & Sentiment Label* indicating the specific assignment. $Controls_i$ includes the following control variables measured in 2023: *Size*, the log of total assets at year-end; *MB*, the total market value of equity divided by book value of equity at year-end; *ROA*, net income divided by ending total assets; *SOE*, an indicator that equals one if the firm's ultimate shareholder is the government, zero otherwise; *Institutional Holdings*, the percentage of shares controlled by institutional investors; *Analysts Following*, the log of one plus the number of analysts following the firm; and *Earnings Surprise*, the difference between actual and mean of analyst forecast EPS, divided by the closing price of the last trading day before the annual report date. We use a Poisson regression model for all estimations. We also control for industry, province, and day fixed effects. Standard errors are clustered by industry.

Table 3, Panel A tabulates the results of the univariate tests. We find that offering an annual report summary during the conference call increases the engagement of investors. Specifically, treatment firms receive a significantly greater number of investor questions compared to control firms (19.86 vs. 14.27, t-stat = 3.54). The number of participants, measured by headcount, is also higher, although the difference is statistically insignificant (t-stat = 0.73).

The regression results are reported in Table 3, Panel B. As shown in column (1), the coefficient on $Treat_i$ is positive and significant at the 1% level. On average, the inclusion of an annual report summary leads to a 46.65% increase in the number of questions posed by investors, as indicated by the comparison to the control group (calculated as $e^{0.383}-1$). The results in column (3) reveal a similar pattern, with the summaries resulting in a 9.41% increase in conference call attendance (calculated as $e^{0.090}-1$), compared to the control group. In column (2), we further examine how the effect varies with the different treatment methods. We observe a significant increase in the number of questions across both treatment groups, and the groups' respective increases are not statistically different (Chi^2-stat=0.05). In column (4), we observe no significant increase in the number of conference call participants when a summary alone is posted, but a significant increase when the summary is accompanied by sentiment labeling. However, once again, the difference between the two treatment groups is not statistically significant (Chi^2-stat=0.32).

The findings suggest that providing a summary of the annual report is associated with increased engagement and more questions by participants. Rather than increasing the number of investors in attendance, the summary appears to mainly impact investors who were already involved in the disclosure event.[31] In the next subsection, we examine how the summaries changed the quality of investors' questions.

4.3 Characteristics of Investors' Questions

4.3.1 Content of the Questions

We examine the question's content. We proxy for information content based on the questions' length (*Length*) and the amount of numerical information *(# of Numbers*). We also test whether the question's content is more likely to come from the topics contained in the summaries (*Alignment*). To identify the topics in the summary, we train Kimi AI to classify each key point into one of the 15 topics. We then used the same method described in Section 4.1 to classify investors' questions into one of the 15 topics.

Before proceeding with the regression results, we present a univariate comparison of the content of investors' questions. Table 4, Panel A reports the frequency of numbers *(# of Numbers*), average length (*Length*), and the degree to which the topics of the investors' questions align with the topics from the summaries (*Alignment*). The questions for treatment firms become 11.7% longer (from 44.30 words to 49.47 words) for the treatment group relative to the control group. Questions for the treatment group are more likely to include numerical content. 40% of the questions in the treatment groups reference numbers compared to 36% in the control group. The differences in the *Length* and *# of Numbers* across the treatment and control groups are statistically significant (t-stat = 8.72 and 2.46, respectively).

[31] Following the taxonomy of Blankespoor et al. (2020), the findings are consistent with the summaries having a greater impact on reducing acquisition and integration costs. Their impact on reducing awareness cost is limited, because if investors had become aware that this disclosure existed, they would have attended it.

We find that questions in the treatment group are more likely to come from topics presented in the summaries. The 50% alignment rate observed in the control group establishes a baseline for the prevalence of questions that are relevant to the annual report's key points. Our analysis reveals a 7% increase in alignment (50% to 57%, with a z-statistic of 8.70) following the introduction of the summaries. The findings suggest that the summaries posted in our experiment direct investor attention to the key topics being presented.

We use regression models to test how posting the summaries affected the content of the questions, using the following model:

Question Content (*Length/# of Numbers/Alignment)* = $\alpha + \beta_1 \, T_i + \sum \beta_n \, Controls_i + \text{FE} + \varepsilon_{i,j}$. (2)

where the outcome variables are the three content variables defined earlier. T_i represents our treatment group assignment for firm *i*: *Treat*, *Summary*, or *Summary & Sentiment Label*. We include the same control variables as specified in equation (1) and account for fixed effects at the industry, province, and day levels. Standard errors are clustered by industry.

Table 4, Panel B presents the regression results. On average, the inclusion of an annual report summary leads to a 14.11% increase in the number of words contained in the questions posed by investors, as indicated by the comparison to the control group (calculated as $e^{0.132}-1$). Also, for treatment firms, the questions raised by investors are 15.7% (calculated as $e^{0.146}-1$) more likely to include numerical content (column (3), Coeff=0.146). The findings suggest that providing a summary to investors can help them utilize more information from annual reports, leading them to ask questions that are more data-driven and informative.

We also find that questions for treatment firms are more likely to come from topics presented in the summary. Specifically, column (5) shows that providing a summary result in a 27.9% (calculated as $e^{0.246} - 1$) greater likelihood that a question's topic aligns with one of the five topics in the annual report summary (t-stat= 3.78). The findings suggest that providing a summary of the annual report focuses investors' questions more on the annual report's key topics, which is consistent with our hypothesis that summaries can influence investors' focus by making key information more salient.

4.3.2 Nature of Investors' Questions

While the greater alignment suggests that investors are actively using the summaries, it does not necessarily indicate improved engagement. It is possible that the questions lack in depth and simply regurgitate facts from the summary. We delve into the nature of the question and test whether it reflects more complex processing on the part of investors asking the question. We use Bloom's taxonomy (Anderson and Krathwohl [2001]), which classifies questions based on their level of cognitive complexity: *Remembering, Understanding, Applying, Analyzing, Evaluating, Creating*.[32] Based on this classification, the basic levels, such as remembering and understanding, represent lower-level cognitive processing. Lower-level questions ask about basic knowledge that is required before one moves onto higher-level cognitive processing (e.g., applying and analyzing) the material. The highest level is to evaluate and synthesize (e.g., make

[32] Studies use Bloom's taxonomy to evaluate the quality of discourse or questions of instructors (Mazzolimi and Maddison 2007) as well as students (Chin and Osborner 2008) in various educational settings. In corporate settings, the taxonomy is adopted by practitioners for organizational learning and knowledge management programs (Amanda 2023).

investment decisions based on the known facts). We present real examples of questions in each classification in Appendix B.

We classify investor questions using Kimi AI.[33] Table 5 Panel A shows the frequency distribution of investors' questions based on Bloom's taxonomy. For treatment firms, the percentage of questions that appear in each level is as follows: *Remembering* (2.50%), *Understanding* (19.72%), *Applying* (3.13%), *Analyzing* (8.26%), *Evaluating* (58.21%), *Creating* (8.16%). Compared to other settings, questions from investors are more likely to involve higher-level cognitive processing (e.g., *Evaluating*) and less frequent lower-level questions (e.g., *Understanding*).[34] When we compare the questions of treatment firms with the control firms, we find that treatment firms have more questions that represent higher-order cognitive complexity (e.g., *Evaluating* 58.2% vs. 52.6%; *Creating* 8.16% vs. 7.03%) and fewer questions with lower cognitive complexity (e.g., *Understanding* 15.67% vs. 19.85%). *Remembering* 2.50% vs. 2.74%). For treatment firms, there is a shift in the distribution of investors' questions from lower-level to higher-level cognitive processing.

We next use an ordered logit model to formally test for changes in the cognitive processing levels of treatment firms' questions.

$$\textit{Bloom's Taxonomy} = \alpha + \beta_1\, Ti + \beta_2\, Ti * Alignment + \beta_3\, Alignment + \sum\beta_n\, Controls_{i,j} + FE + \varepsilon_{i,j} \quad (3)$$

[33] We use the following prompt, "Please analyze which dimensions of Bloom's Taxonomy (2001 revised edition) the following question belongs to, and rank the two most likely dimensions in order." We use the dimensions with the highest rank order.
[34] Prior studies using Bloom's taxonomy in educational settings show that most questions target lower-order cognitive skills than higher-order skills (Metzgar 2023).

The dependent variable, Bloom's Taxonomy, is an ordinal variable that takes values from 1 to 6, corresponding to the cognitive level of the questions (*Remember* (1), *Understand* (2), *Apply* (3), *Analyze* (4), *Evaluate* (5), and *Create* (6)). *Ti* is an indicator for firm's assigned treatment group (*Treat*, *Summary*, or *Summary & Sentiment Label). Alignment* is an indicator variable for questions that raise topics that match the topics presented in the summary. We include the same control variables as specified in equation (1) and account for fixed effects at the industry, province, and day levels. Standard errors are clustered by industry.

Table 5, Panel B reports the regression results. On average, the inclusion of an annual report summary is associated with a 37.8% increase in cognitive complexity, as measured by Bloom's taxonomy (calculated as $e^{0.321} - 1$). To test whether this increase is more pronounced when investor questions directly reference the summary, we include an interaction term (*Alignment* × *Treat*). In Column (3), we find a 12.3% greater increase in cognitive complexity ($e^{0.116} - 1$) for treatment firms when questions are aligned with the summary content. These results suggest that providing a summary encourages investors to engage more deeply with the report, prompting them to generate higher-quality questions rather than simply restating facts (Elliott, Grant, and Hobson [2020]).

4.3.3 Cross-sectional tests

We test whether investors use the summary more when they face greater information processing costs in the annual reports. We examine whether investors rely more on the summaries when the annual reports impose greater processing costs. Following prior literature, we use the length of the annual report (Li [2008]; Dyer, Lang, and Stice-Lawrence [2017]) and annual report sentiment (Loughran and McDonald [2011]) to proxy for the investors' processing burden. We examine whether the investors rely on the summaries when the reports are long and contain a more negative tone.

Table 6 reports the results from the cross-sectional tests. We partition the sample into terciles based on annual report length (columns (1) to (3)), where longer reports present a greater information processing cost. We use the annual report sentiment (columns (4) to (6)) and consider negative sentiment to impose greater processing costs. The positive and negative word lists are derived from the dictionary provided by Loughran and McDonald (2011).[35] We use the count of negative and positive words in the annual reports. We measure negative sentiment based on the difference in the number of negative and positive words, scaled by the sum of the number of positive words and negative words.

Table 6 presents the estimated coefficients on the *Treatment* variable. We find that investors from treatment firms are more likely to ask aligned questions when the annual report is long (Column (1), Coeff = 0.442, z-stat=4.16), and thus face greater information processing costs, than when the reports are short (Column (3), Coeff = 0.252, z-stat=4.66). We also find systematic effects across annual report sentiment. Investors in treatment firms are more likely to raise aligned questions when the sentiment of the annual report is negative (Column (4), Coeff = 0.422, z-stat=4.92) than positive (Column (6), Coeff = -0.037, z-stat=-0.43). The

[35] We use the value provided by the Chinese Research Data Services database, which uses a translated version of the dictionary provided in Loughran and McDonald (2011).

differences in the estimated coefficients are statistically significant for both partitions (Chi^2 = 3.12 and 18.77, respectively).

Next, we test whether investors raise aligned questions during calls when investors actively clicked on the summary link. We partition the sample into terciles based on the number of investors' clicks. The click allows us to directly observe investors' use of the summary. We find that aligned questions are most likely to occur when there were frequent clicks (Column (7), Coeff = 0.356, z-stat=4.49). The treatment effects are also statistically significant in the subsample where the clicks were infrequent (Column (9), Coeff = 0.164, z-stat=2.39), the magnitudes are much weaker compared to the subsample where there were frequent clicks (Chi^2 = 7.78). The findings suggest that the aligned questions indeed originate from investors' active use of the summary information.

4.3.4 Conditional on Investor Type

To examine whether the treatment effects on participation and question content differ across various investor groups, we further partition our sample based on specific investor characteristics. Participants can register on the Quanjing platform using either their citizen ID card or phone number. Quanjing assigns a registered ID to those who authenticate using a citizen ID card, but uses the phone number to identify those who use their phone number for authentication. Due to security reasons and requirements from the IRB, we were provided with participants' registered IDs (anonymized) but not their phone numbers. In our analysis of investor identity, we thus use 6,213 investors with registered IDs. These investors posed 13,726 questions, which represents 68.52% of the total sample of 20,031 questions. The following analysis is based on participants' anonymized IDs.

We first categorize investors based on whether they asked a question during any Quanjing platform conference call in 2022. We predict that silent investors—those that did not ask any questions in 2022—are less experienced and may therefore benefit more from the annual report summaries, leading them to ask more questions going forward. In contrast, we expect that vocal investors—those who asked one or more questions in 2022—are more experienced, so that the summaries will have a weaker effect on them.

The regression results are presented in Table 7, Panel A. Column (1) shows that silent investors do tend to ask more questions (Coeff = 0.249, z-stat=2.34) after being provided a summary of the annual report in 2023. In column (3) for vocal investors, we also observe a positive increase in the number of questions for treatment groups (Coeff = 0.145, z-stat=1.96) but with less economic significance. This suggests that the annual report summaries also stimulate questioning by vocal investors, but to a lesser extent.

Next, we explore whether the influence of the annual report summaries differs by investor type. Table 7, Panel B, presents the outcomes of this analysis. In column (1), the coefficient on *Treat* (Coeff. = 0.157) is positively significant, indicating that silent investors in the treatment group are more inclined to ask questions on topics that align with the topics in the summaries (relative to silent investors in the control group). More intriguingly, in column (3), the coefficient on *Treat* (Coeff. = -0.168) is significantly negative. This suggests that vocal investors in the treatment group tend to ask fewer questions that align with the topics in the summaries, and instead focus more on other topics.

The findings suggest that the summaries guide less experienced investors to ask more questions. While increased participation by these investors would seem likely to displace questions by experienced investors, we find that it does not. Rather, the increased participation of the inexperienced appears to make the experienced investors consider—and ask about—topics that go beyond the key points of the annual report. Next, we examine how both aligned and non-aligned questions impact the overall quality of the Q&A dialogue.

4.4 The Quality of Managers' Responses

In this section, we investigate how providing annual report summaries affects the quality of managers' responses to investor questions. While the summaries encourage greater investor engagement, their impact on the overall quality of the call remains ambiguous because firms can avoid clearly answering the questions. To assess the implications of our intervention on the quality of the interaction, we focus on two aspects: the quality of the firms' responses to investors' questions, and the capital market effects around the conference calls.

To evaluate the quality of firms' responses, we use two metrics: *Length_re*, which measures the response length by word count; and *Informative*, an AI-based measure of the comprehensiveness and quality of a firm's response.[36] We assess the response quality based on a scale from one to five using the following criteria: directness in addressing the investors'

[36] We train Kimi AI to evaluate the quality of the firm's responses using a training sample of 500 randomly selected responses. The model's out-of-sample accuracy is 93% when verified against a hold-out sample based on manual coding.

questions; provision of detailed information, including numerical data and supporting evidence; and the firm's attitude in responding. We define *Informative* as equal to one if the response receives a rating above the median score of three, zero otherwise.

Table 8, Panel A presents the results of the univariate tests. We find that the treatment firms' answers are 11.4% longer (341.90 vs. 306.86 words) on average than the control firms' answers. Moreover, the treatment firms' answers are more informative (=0.44 vs. 0.41, z-stat = 3.75). The regression analyses confirm these findings. We replace the outcome variable with the quality metrics *Length_re* and *Informative* and re-estimate Equation (2). For *Length_re*, we use a Poisson regression model, and for *Informative*, we use a logit model. The regression results are reported in Table 8, Panel B. In column (1), the coefficient on *Treat* is positive and significant at the 1% level, indicating that providing annual report summaries leads to longer answers from firms. Column (3) shows a similar finding using the *Informative* measure.

Was the improvement in the manager's response due to managers being better prepared?

One possible alternative for the enhanced quality of managers' responses is that managers are better prepared to address questions from the summary topics. In our experiment, managers were made aware of the summary at the same time as the investors, which was when the ECCs' call announcements went out. Firms typically hold their ECCs 7 days after the announcement day, on average, but the window varies across firms. It is possible that some firms had a longer window to prepare themselves for the topics provided in the summary. We try to rule out this alternative in two ways.

First, we examine whether the increase in response quality varied based on how long the summaries were made public before the call. If the improved response quality was due to managers being better prepared, we expect that the effect on managers' response may be greater among firms that had a longer time lag between the ECC announcement and the calls, and managers had more time to prepare. In Table 8, Panel C, we divide the sample into two groups based on the time interval between the ECC call announcement and the call. The results indicate that the coefficient is significantly positive (Coeff. = 0.120, t-stat = 4.51) for conference calls where managers have more time to prepare (Column 1), but even more significant (Coeff. = 0.136, t-stat = 6.17) for conference calls where managers have less time to prepare (Column 2). However, the difference between these coefficients is not statistically significant (Diff. = -0.016, Chi^2 = 0.87). We fail to find systematic variation in response quality across managers' preparation time. These results alleviate the earlier concern that the improved quality of managers' responses might be due to their better preparation for topics from the summary.

Second, we test whether the response quality differs between questions that ask about topics from the summary (aligned) and those that ask about topics outside of the summaries (not-aligned). If managers provide information because they are better prepared for the topics, the quality of responses will improve only for aligned questions.

Table 8, Panel D, shows the estimated results after partitioning the sample into aligned questions and non-aligned questions. We find that all questions, regardless of alignment, experience a significant improvement in response quality. In Columns (1) and (2), we find a significant increase in length of both aligned (=0.141, t-stat= 6.05). and non-aligned questions

(=0.100, t- stat = 3.64). Although the effect is slightly less pronounced for non-aligned questions, the difference is not statistically significant (Chi^2 =1.60). Columns (3) and (4) further substantiate this finding. The improvement in response quality for both types of questions indicate an overall enhancement in the quality of the conference call, rather than managers selectively preparing for questions that may arise from the summary topics.

4.5 Capital Market Effects

We examine market-wide effects to assess whether providing the summaries helps conference calls generate information for the market. We first focus on stock market movement, reflected by two key variables: *Turnover*, the cumulative turnover ratio (the number of shares traded divided by the number of shares outstanding) from one day before to five days after the conference call; and *Abs_CAR*, the absolute value of cumulated abnormal returns over the same period. Abnormal returns are calculated using the market model of raw returns minus market returns. Table 9, Panel A, shows the estimated results. For the treatment group, we observe a significant increase in *Turnover* (Coeff. = 0.021, t-stat = 1.91). Although the *Abs_CAR* increases, the change is not statistically significant (Coeff. = 0.004, t-stat = 0.74).

We examine whether the impact of summaries on market returns is greater when more investors actively engage in conference calls. We divide the sample into terciles based on the number of investor questions in Panel B. Our results show a significant increase in Abs_CAR (Coeff. = 0.015, t-stat = 3.37) when the conference calls received the highest number of investor questions. Conversely, the treatment effects are much weaker and insignificant when fewer questions are asked. These findings suggest that summaries enhance the informational value of conference calls for the market, provided that the calls attract sufficient investor participation.

Next, we examine the post-conference call activity of retail investors. If our summaries effectively engage retail investors, the investors should be more inclined to communicate with firms not only during the conference call but also in the days that follow. To capture this momentum, we monitor the interactions between investors and firms on online platforms. We collect all questions that investors raised about the sample firm around the conference call date, then count the number of questions raised from 0 to 30 days (and up to 90 days) post conference call. Table 9, Panel C, presents the estimated results. For the treatment group, we observe a significant increase in posts following the calls (coefficient = 0.061, t-stat = 3.34). We conclude that providing summaries leads to an increase in investors' incentive to engage with firms immediately following the calls.

5. CONCLUSION

We use a field experiment to examine whether providing investors with AI-generated annual report summaries during virtual conference calls enhances firm-investor interaction. Our experiment results show that providing the summaries significantly increases the number of questions raised, and that the content of these questions becomes longer, more analytical, and address issues requiring higher-level cognitive processing.

Questions are more likely to address topics covered in the summaries, particularly when investors face a greater cost to process the annual report. Providing summaries has a greater effect on investor engagement when investors are less experienced and faced with greater processing costs (i.e., longer annual report with negative sentiment). Providing the summaries also increases the number of questions from experienced investors, though they tend to focus more on topics not covered by the summaries.

Our evidence further reveals that the summaries also improve firms' responses to investor questions. We find that firms provide longer and more detailed responses when investors are given the summaries. This effect is observed for both topically aligned and non-aligned questions, suggesting that the quality of exchanges improves even for topics not covered in the summaries. We find that stronger market reaction to calls of treatment firms, suggesting that investors are more likely to rely on the annual report content after greater engagement. Treatment firms experience greater trading volume of the firms' shares from one day before to five days after the calls, and a stronger market response for firms that experienced greater engagement. Overall, these results suggest that AI-generated summaries can increase investor engagement and lead to more informative responses from firms during conference calls.

References

Anderson, L. W., and D.R. Krathwohl, eds. *Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives*. New York: Longman, 2001.

Amanda, L. (2023). *Implementing Bloom's taxonomy in corporate knowledge management programs: A case study*. Internal report, Knowledge Management Division.

Atkinson R. C., Shiffrin R. M. (1968). Human memory: a proposed system and its control processes, *The psychology of learning and motivation: Advances in research and theory 2nd ed*. eds. 89–195.

Barber, B.M., Odean, T., (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21, 785-818

Bian, S., Li, F., Yan, Z. (2021). Do Retail Investors Matter?. *Available at SSRN* 3861763.

Blankespoor, E. (2019). The impact of information processing costs on firm disclosure choice: Evidence from the XBRL mandate. *Journal of Accounting Research*, *57*(4), 919-967.

Blankespoor, E., deHaan, E., & Marinovic, I. (2020). Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics*, *70*(2-3), 101344.

Bonsall IV, S. B., Leone, A. J., Miller, B. P., & Rennekamp, K. (2017). A plain English measure of financial reporting readability. *Journal of Accounting and Economics*, *63*(2-3), 329-357.

Brochet, F., Chychyla, R., & Ferri, F. (2023). Virtual Shareholder Meetings. *Management Science* 70(9):5896-5930.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2015). Inside the "Black Box" of Sell-Side Financial Analysts. Journal of Accounting Research, 53(1), 1–47.

Bushee, B. J., & Miller, G. S. (2012). Investor relations, firm visibility, and investor following. *The Accounting Review*, 87(3), 867–89.

Bushman, R. M., Gigler, F., & Indjejikian, R. J. (1996). A model of two-tiered financial reporting. *Journal of Accounting Research*, 34, 51-74

Cardinaels, E., Hollander, S., & White, B. J. (2019). Automatic summarization of earnings releases: attributes and effects on investors' judgments. Review of Accounting Studies, 24, 860-890.

Cheng, Q., L. Hail, and G., Yu, (2022), The past, present, and future of China-related accounting research, *Journal of Accounting and Economics* 74(2–3).

Cheng, L., D.T. Roulstone, and A. Van Buskirk (2021), Are Investors Influenced by the Order of Information in Earnings Press Releases?. *The Accounting Review* 96 (2): 413–433.

Chin, C., & Osborne, J. (2008). Students' questions: A potential resource for teaching and learning science. *Studies in Science Education*, 44(1), 1–39

Choi, J. K., Huang, A. H., Qiu, L., & Zheng, Y. (2024). Investor Relations for the Rest of Us: Engaging with Retail Investors. *Available at SSRN.*

Croom, J., Grant, S. M., & Seto, S. C. (2023). Q&A interactions: Giving investors a voice and managers' withholding of information. *Available at SSRN 4508135*.

Darendeli, A. (2024). How do retail investors respond to summary disclosure? Evidence from mutual fund factsheets. *Review of Accounting Studies*, 1-45.

deHaan, E., Madsen, J. and Piotroski, J.D., 2017. Do Weather-Induced Moods Affect the Processing of Earnings News? *Journal of Accounting Research*, 55(3), pp.509-550.

Dyer, T., Lang, M., & Stice-Lawrence, L. (2017). The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics*, *64*(2-3), 221-245.

Elliott W.B., Grant S.M., Hobson J.L. (2020) Trader Participation in Disclosure: Implications of Interactions with Management. *Contemporary Accounting Research*, 37 (1), 68 – 100.

Gao, M., & Huang, J. (2020). Informing the market: The effect of modern information technologies on information production. *The Review of Financial Studies*, *33*(4), 1367-1411.

Goldstein, I., Yang, S., & Zuo, L. (2023). The real effects of modern information technologies: Evidence from the EDGAR implementation. *Journal of Accounting Research*, *61*(5), 1699-1733.

Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, *70*(3), 393–408.

Hirshleifer, D., Lim, S. S., & Teoh, S. H., (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, 64(5), 2289-2325.

Hirshleifer, D. & Teoh, S.H. (2003). Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics*, 36(1–3).

Kim, A., Muhn, M., & Nikolaev, V. (2024). Bloated Disclosures: Can ChatGPT Help Investors Process Financial Information?. *arXiv preprint arXiv*:2306.10224.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, 45(2–3), 221–247.

Liu, Y., & Wang, H. (2024). Who on Earth Is Using Generative AI?. *Policy Research Working Paper* No. 10870. Washington, DC: World Bank

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1), 35–65.

Maines, L. A., & McDaniel, L. S. (2000). Effects of Comprehensive-Income Characteristics on Nonprofessional Investors' Judgments: The Role of Financial-Statement Presentation Format. *The Accounting Review*, *75*(2), 179–207.

Markov, S., & Yezegel, A. (2023). Giving Retail Investors a Say in Disclosure. *Available at SSRN 4836378*.

Mayew, W. J. (2008). Evidence of Management Discrimination among Analysts during Earnings Conference Calls. *Journal of Accounting Research*, 46(3), 627–659

Mayew, W. J., Sethuraman, M., & Venkatachalam, M. (2020). Individual Analysts' Stock Recommendations, Earnings Forecasts, and the Informativeness of Conference Call Question and Answer Sessions. *The Accounting Review* 95(6):311-337.

Mazzoleni, M., & Maddison, S. (2007). Evaluating the quality of instructional discourse using Bloom's taxonomy. *Educational Research and Review*, 2(3), 45–51.

Metzgar, M. 2023 Revised Bloom's Taxonomy in a Principles of Economics Textbook. *Acta Educationis Generalis* 13(3) Sciendo, pp. 15-28.

Securities and Exchange Commission (1995). "Use of Abbreviated Financial Statements in Document Delivered to Investors Pursuant to the Securities Act of 1933 and Securities Act of 1934." Rule Proposal.

Triplett, N. (1898). The dynamogenic factors in pacemaking and competition. *The American journal of psychology*, *9*(4), 507-533.

Wong, T. J., Yu, G., Zhang, S., & Zhang, T. (2024). Calling for transparency: Evidence from a field experiment. *Journal of Accounting and Economics*, *77*(1), 101604.

Zajonc, R. B. (1965). Social Facilitation: A solution is suggested for an old unresolved social psychological problem. *Science*, *149*(3681), 269-274.

Table 1: Pre-experiment Randomization

Before the experiment, we randomly assigned 30% of firms to the control group and 35% of firms to each of the two treatment groups—*Summary* and *Summary & Sentiment Label*—according to the list of firms that had used the Quanjing platform for their 2022 annual report conference calls. We randomly assigned firms that were new participants on the Quanjing platform in 2023 to one of the three groups once their conference call dates were confirmed with the platform. Panel A presents this sample selection process. Panel B presents the covariate balance between the treatment and control groups. We report the means for variables such as the log of total assets at year-end (*Size*), return on assets (*ROA*), a binary variable indicating whether the firm is state-controlled (*SOE*), the percentage of shares held by institutional investors (*Institutional Holdings*), the number of analysts covering the firm (*Analysts Following*), and the difference between actual and mean analyst forecast EPS, divided by the closing price on the last trading day before the annual report date (*Earnings Surprise*). We present the average number of each characteristic with T-statistics in parentheses for testing the difference. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Final Sample

Groups	Listed firms	Percentage (%)	Preassigned	New
Control	343	31.04	246	97
Treatment1: Summary only	373	33.76	277	96
Treatment 2: Summary & Sentiment	389	35.20	292	97
In Total	1,105	100.00	815	290

Panel B: Balance Test of the Final Sample

	Control	Summary	Summary & Sentiment Label
	(1)	(2)	(3)
Size	22.20	22.05	22.04
		(1.37)	(1.46)
ROA	0.03	0.03	0.03
		(0.90)	(-0.31)
SOE	0.13	0.15	0.10
		(-1.06)	(1.31)
Institutional holdings	0.37	0.36	0.34
		(0.28)	(1.16)
Analysts following	5.33	4.34	4.54
		(1.57)	(1.26)
Earnings surprise	-0.02	-0.02	-0.02
		(-1.10)	(-0.60)
# of firms	343	373	389

Table 2: Description of the Annual Report Summary by Topic and Sentiment

Panel A: Distribution of Topics

Panel A presents the distribution of topics of the annual report summary for the conference call separately for the treatment and control samples. The only difference for control firms is that we did not post the summary publicly to investors. We instructed Kimi to classify each of the key points into one of 15 predefined topics: Financial Information, Production Management, Product Markets, Supply Chain, Innovation, Risks, Government Policy, ESG, Financing, Strategy, Payout, Business Cooperation, Investors' Relationship, Capital Market, and Others.

	CONTROL		TREATMENT	
Topics	Frequency	Percent (%)	Frequency	Percent (%)
1.Financial Information	447	26.06	1,001	26.27
2.Production Management	70	4.08	149	3.91
3.Product Markets	301	17.55	362	9.50
4.Supply Chain	28	1.63	45	1.18
5.Innovation	314	18.31	665	17.45
6.Risks	257	14.99	530	13.91
7.Government Policy	8	0.47	19	0.50
8.ESG	88	5.13	294	7.72
9.Financing	59	3.44	196	5.14
10.Strategy	83	4.84	354	9.29
11.Payout	52	3.03	164	4.30
12.Business Cooperation	4	0.23	12	0.31
13.Investors' Relationship	3	0.17	9	0.24
14.Capital Market	1	0.06	3	0.08
15.Others	0	0.00	7	0.18
Total	1,715	100.00	3,810	100.00

Panel B: Distribution of Sentiment

Panel B presents the distributions of sentiments of all key points separately for the treatment and control samples. We also manually assigned a sentiment label (positive, neutral, or negative) to each of the summary points.

	CONTROL		TREATMENT	
Topics	Frequency	Percent (%)	Frequency	Percent (%)
Negative	192	11.19	413	10.84
Neutral	308	17.96	723	18.98
Positive	1,215	70.85	2,674	70.18
Total	1,715	100.00	3,810	100.00

Table 3: Summary and Investor Engagement

Panel A: Univariate Test

This table presents the difference between treatment and control firms in investors' level of participation during the conference call. We measure investors' level of participation using two variables: *Questions*, the number of questions submitted by participants through the online platform; and *Participants*, the total headcount of individuals who joined the conference call. *T-stat*istics of difference tests are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Outcomes	Control	Treatment	Difference (T-C)
N	343	762	
Questions	14.27	19.86	5.59***
			(3.54)
Participants	197.19	209.97	12.78
			(0.73)

Panel B: Regression

This table reports the Poisson regression results from estimating the following model using firm-level data:

$$\text{Poisson}(\text{Questions}_i \text{ or Participants}_i) = \alpha + \beta_1 T_i + \sum \beta_n \text{Controls}_i + \text{FE} + \varepsilon_i$$

In these estimations, the outcome variable $Questions_i$ is measured by counting the number of questions submitted by participants through the online platform during the conference call for firm i. $Participants_i$ is measured as the total headcount of individuals who joined the conference call for firm i. T_i represents the randomly assigned treatment groups of firm i, including *Treat*, *Summary*, and *Summary & Sentiment Label*. $Controls_i$ includes the following control variables measured in 2023: *Size*, the log of total assets at year-end; *MB*, the total market value of equity divided by book value of equity at year-end; *ROA*, net income divided by ending total assets; *SOE*, an indicator equal to one if the firm's ultimate shareholder is the government, zero otherwise; *Institutional Holdings*, the percentage of shares controlled by institutional investors; *Analysts Following*, the log of one plus the number of analysts following the firm; and *Earnings Surprise*, the difference between actual and mean of analyst forecast EPS, divided by the closing price of the last trading day before the annual report date. Industry FEs, province FEs, and day FEs are included in all columns. *Z-stat*istics from Wald Tests are reported in parentheses. Standard errors are clustered by industry. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Questions		Participants	
	(1)	(2)	(3)	(4)
Treat	0.383***		0.090**	
	(3.97)		(2.04)	
Summary		0.378***		0.065
		(4.41)		(0.83)
Summary & Sentiment Label		0.388***		0.115***
		(3.53)		(2.64)
Size	0.206*	0.206*	0.282***	0.281***
	(1.90)	(1.91)	(4.37)	(4.30)
MB	0.067***	0.067***	0.078***	0.078***

	(3.05)	(3.04)	(3.66)	(3.64)
ROA	0.293	0.291	-0.335	-0.341
	(0.39)	(0.39)	(-0.39)	(-0.40)
SOE	0.015	0.015	0.003	0.005
	(0.14)	(0.14)	(0.08)	(0.11)
Institutional holdings	-0.047	-0.046	-0.048	-0.044
	(-0.31)	(-0.31)	(-0.37)	(-0.34)
Analysts following	0.055	0.055	0.057	0.057
	(1.10)	(1.10)	(1.23)	(1.23)
Earnings surprise	1.698	1.701	0.613	0.620
	(1.12)	(1.11)	(0.62)	(0.62)
H0: T1-T2		-0.010		-0.050
		(0.05)		(0.32)
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
# of Observations	1,105	1,105	1,105	1,105
R-squared	0.20	0.20	0.48	0.48

Table 4: Content of Investor Questions

Panel A: Univariate Test

This table presents the characteristics of investors' questions across treatment and control firms. *Length* is the number of words contained in the question. *# of Numbers* is the amount of numerical information contained in the question. *Alignment* is a binary indicator that equals one if the topic of an investor's question matches any of the five key points' topics, zero otherwise. All analyses are conducted at the question level. T-statistics of difference tests are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Treatment		Control		Difference (T-C)
	N	*Mean*	N	*Mean*	
Length	15,139	49.47	4,892	44.30	5.17***
					(8.72)
# of Numbers	15,139	0.40	4,892	0.36	0.04**
					(2.47)
Alignment	15,139	0.57	4,892	0.50	0.07**
					(8.70)

Panel B: Content of Investor Questions

This table reports the regression results from estimating the following model using question-level data:

$$\text{Model}(\mathit{Length}, \#\ \mathit{of\ Numbers}, \mathit{Alignment}) = \alpha + \beta_1 T_i + \sum \beta_n \mathit{Controls}_i + \text{FE} + \varepsilon_i$$

The dependent variable *Length* is the number of words contained in the question. *# of Numbers* is the amount of numerical information contained in the question. *Alignment* is an indicator variable that equals one if the topic of an investor's question matches any of the five key points' topics, zero otherwise. T_i represents our treatment group assignment for firm i: *Treat*, *Summary*, or *Summary & Sentiment Label*. We use Poisson regressions for models (1) to (4) and logit regressions for models (5) and (6). Control variables are identical to Table 3 Panel B. Industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. Z-statistics from Wald Tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	*Length*		*# of Numbers*		*Alignment*	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.132***		0.146**		0.246***	
	(3.45)		(2.27)		(3.78)	
Summary		0.123***		0.155*		0.201***
		(2.72)		(1.67)		(3.03)
Summary & Sentiment Label		0.140***		0.137**		0.293***
		(4.26)		(2.22)		(3.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	20,031	20,031	20,031	20,031	20,031	20,031
R-squared	0.06	0.06	0.06	0.06	0.01	0.01

Table 5: Nature of Investor Questions

Panel A: Univariate Test

This table presents the level of cognitive processing based on Bloom's taxonomy (Anderson and Krathwohl 2001).

	CONTROL		TREATMENT	
Topics	Frequency	Percent (%)	Frequency	Percent (%)
Remembering	134	2.74	379	2.50
Understanding	1,284	26.25	2,986	19.72
Applying	178	3.64	474	3.13
Analyzing	377	7.71	1,251	8.26
Evaluating	2,575	52.64	8,813	58.21
Creating	344	7.03	1,236	8.16
				-
Total	4,892	100.00	15,139	100.00

Panel B: Nature of Investor Questions Based on Bloom's Taxonomy

This table reports the regression results from estimating the following model using interaction-level data:

$$\text{Logit (Bloom's Taxonomy)} = \alpha + \beta_1 \text{ Ti} + \beta_2 \text{ Ti} * \text{Alignment} + \beta_3 \text{ Alignment} + \sum \beta_n \text{Controls}_{i,j} + \text{FE} + \varepsilon_{i,j}$$

The dependent variable, Bloom's Taxonomy, is an ordinal variable that takes values from 1 to 6, corresponding to the cognitive processes of Remember, Understand, Apply, Analyze, Evaluate, and Create, respectively. *Ti* represents the firm's randomly assigned treatment group: *Treat*, *Summary*, or *Summary & Sentiment Label*. Control variables, industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. Ordered logit regressions are applied to all columns. *Z-stat*istics from Wald Tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Bloom's Taxonomy		
	(1)	(2)	(3)
Treat	0.321***		0.251***
	(11.42)		(4.97)
Summary		0.323***	
		(14.89)	
Summary & Sentiment Label		0.319***	
		(7.63)	
Alignment * Treat			0.116*
			(1.66)
Alignment			0.074
			(1.09)
Controls	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes
# of Observations	20,031	20,031	20,031
R-squared	0.01	0.01	0.01

Table 6 Cross-sectional tests

This table reports the regression results from estimating the following model using question-level data, using the full sample:

$$\text{Logit}\ (Alignment_{i,j}) = \alpha + \beta_1\ T_i + \sum \beta_n\ Controls_i + \text{FE} + \varepsilon_i$$

In the estimation, the dependent variable *Alignment* is an indicator variable that equals one if the topic of an investor's question matches any of the five key points' topics, zero otherwise. T_i represents our treatment group assignment for firm *i*: *Treat*, *Summary*, or *Summary & Sentiment Label*. We partition the sample into terciles based on (i) annual report length, and (ii) tone of the annual report, and (iii) frequency of investor's clicks. We use Poisson regressions for all models. Control variables are identical to Table 3 Panel B. Industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. *Z-stat*istics from Wald Tests are reported in parentheses. Chi^2 statistics from F-Tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dependent Variable:	Alignment								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Annual report length			Annual report sentiment			Frequency of clicks	
	Long	Medium	Short	Positive	Neutral	Negative	Frequent	Medium	Infrequent
Treat	0.442***	0.262***	0.252***	-0.037	0.219***	0.422***	0.356***	0.214***	0.164**
	(4.16)	(4.49)	(4.66)	(-0.43)	(3.52)	(4.92)	(4.49)	(3.30)	(2.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE, Province FE and Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test	Long = Short	0.190*		Positive = Negative	-0.459***		Frequent = Infrequent	0.192***	
		(3.12)			(18.77)			(7.78)	
# of Observations	6,072	7,929	6,030	9,454	9,454	6,030	6,126	7,910	5,995
R-squared	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.04

Table 7: Changes in Engagement by Investor Type

Panel A: Number of Questions Raised by Silent versus Vocal Investors

This table reports the regression results from estimating the following model using question-level data:

$$\text{Poisson } (Questions_i) = \alpha + \beta_1 T_i + \sum \beta_n Controls_i + FE + \varepsilon_i$$

In these estimations, the outcome variable $Questions_i$ is measured by counting the number of questions submitted by participants through the online platform during the conference call for firm i. T_i represents the randomly assigned treatment group of firm i: *Treat*, *Summary*, or *Summary & Sentiment Label*. In columns (1) and (2), we use the number of questions raised by silent investors (i.e., investors who did not ask any questions in the 2022 (the prior year) conference calls), while in columns (3) and (4) we use the number of questions raised by vocal investors (i.e., investors who asked questions in the 2022 conference calls). The Poisson regression model is applied to all columns. Industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. Z-statistics from Wald Tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Questions		Questions	
	(1)	(2)	(3)	(4)
	Silent Investors		Vocal Investors	
Treat	0.249**		0.145*	
	(2.34)		(1.96)	
Summary		0.254**		0.154***
		(2.57)		(2.72)
Summary & Sentiment Label		0.245**		0.137
		(2.09)		(1.12)
Controls	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
# of Observations	1,091	1,091	1,091	1,091
R-squared	0.15	0.15	0.17	0.17

Panel B: Alignment Conditional on Silent versus Vocal Investors

This table reports the regression results from estimating the following model using question-level data, using the full sample:

$$\text{Logit } (Alignment_{i,j}) = \alpha + \beta_1 T_i + \sum \beta_n Controls_i + FE + \varepsilon_i$$

In the estimation, the dependent variable $Alignment_{i,j}$ is a binary indicator that equals one if the topic of an investor's question j matches any of the five key points' topics from firm i's annual report, zero otherwise. T_i represents our treatment group assignment for firm i: *Treat*, *Summary*, or *Summary & Sentiment Label*. In columns (1) and (2), we use the questions raised by silent investors (i.e., investors who did not ask any questions in the 2023 (the prior year) conference calls), while in columns (3) and (4) we use the questions raised by vocal investors (i.e., investors who asked questions in the 2023 conference calls). The logit regression model is applied to all columns. Industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. Z-statistics from Wald Tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Alignment		Alignment	
	(1)	(2)	(3)	(4)
	Silent Investors		Vocal Investors	
Treat	0.157**		-0.168***	
	(2.48)		(-3.02)	
Summary		0.115*		-0.192***
		(1.82)		(-3.52)
Summary & Sentiment Label		0.199***		-0.143*
		(2.63)		(-1.76)
Controls	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
# of Observations	11,370	11,370	2,366	2,366
R-squared	0.02	0.02	0.05	0.05

Table 8: The Quality of Firms' Responses

Panel A: Univariate Test

This table presents the difference in firms' response quality between treatment and control firms. In this estimation, the dependent variable *Length_re* is the total number of words contained in a response. *Informative* is an indicator variable that equals one if a response receives an AI-generated rating above the median score of three, zero otherwise. All analyses are conducted at the question level. T-statistics of difference tests are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Length_re	Control	Treatment	Difference (T-C)
	306.86	341.90	35.04**
			(7.01)
Informative			
	0.41	0.44	0.03***
			(3.75)

Panel B: Regression

This table reports the regression results from estimating the following model using question-level data:

$$\text{Poisson}(\text{Length\_re}_{i,t}) \,/\, \text{Logit}(\text{Informative}_{i,t}) == \alpha + \beta_1 \text{ Ti} + \sum \beta_n \text{Controls}_{i,t} + \text{FE} + \varepsilon_{i,t}$$

In this estimation, the dependent variable *Length_re* is the total number of words contained in a response. *Informative* is an indicator variable that equals one if a response receives an AI-generated rating above the median score of three, zero otherwise. *Ti* represents the firm's randomly assigned treatment group: *Treat*, *Summary*, or *Summary & Sentiment Label*. The Poisson model is reported in columns 1 and 2, and the Logit model is reported in columns 3 and 4. Control variables, industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. *Z-stat*istics from Wald Tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Length_re		Informative	
	(1)	(2)	(3)	(4)
Treat	0.127***		0.146***	
	(5.87)		(2.94)	
Summary		0.135***		0.176**
		(4.77)		(2.04)
Summary & Sentiment Label		0.118***		0.114*
		(4.50)		(1.91)
Controls	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
# of Observations	17,417	17,417	17,417	17,417
R-squared	0.07	0.07	0.02	0.02

Panel C: Conditional on how long the summaries were made public before the call

This table reports the regression results from estimating the following model in Table 8 Panel B using question-level data. We split the sample into two equal parts, based on the time interval between the posting of the summary and the conference call. The dependent variable *Length_re* is the total number of words in a response. *Informative* is an indicator variable that equals one if a response receives an AI-generated rating above the median score of three, zero otherwise. *Treat* is an indicator variable for questions from firms assigned to the treatment group. The Poisson model is reported in columns 1 and 2, and the logit model is reported in columns 3 and 4. Control variables, industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. *Z-stat*istics from Wald Tests are reported in parentheses. Chi^2 statistics from F-Tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Length_re		Informative	
	(1)	(2)	(3)	(4)
	More time	Less time	More time	Less time
Treat	0.120***	0.136***	0.149**	0.179***
	(4.51)	(6.17)	(2.23)	(3.67)
H1: More-Less	-0.016		-0.030	
	(0.87)		(0.40)	
Controls	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
# of Observations	11,295	10,649	11,287	10,649
R-squared	0.09	0.09	0.03	0.04

Panel D: Conditional on whether the questions were aligned with the summary topic

This table reports the regression results from estimating the model in Table 8 Panel B using question-level data. We partition the sample into two equal parts based on whether the questions were considered to be aligned (columns 1 and 3) and not-aligned (Columns 2 and 4). Aligned questions are defined as questions that raise topics that match the topics covered in any of the five key points' topics from the firm's annual report. The dependent variable *Length_re* is the total number of words in a response. *Informative* is an indicator variable that equals one if a response receives an AI-generated rating above the median score of three, zero otherwise. *Treat* is an indicator variable for questions from firms assigned to the treatment group. The Poisson model is reported in columns 1 and 2, and the logit model is reported in columns 3 and 4. Control variables, industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. *Z-stat*istics from Wald Tests are reported in parentheses. Chi^2 statistics from F-tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Length_re		Informative	
	(1)	(2)	(3)	(4)
	Aligned	Not-aligned	Aligned	Not-aligned
Treat	0.141***	0.100***	0.160***	0.115*
	(6.05)	(3.64)	(2.94)	(1.93)
H1: Aligned-Not-Aligned	0.041		0.045	
	(1.60)		(0.18)	
Controls	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
# of Observations	9,708	7,709	9,708	7,709
R-squared	0.07	0.09	0.03	0.03

Table 9: Market-wide effects

Panel A: Capital Market

This table reports the OLS regression results from estimating the following model using firm-level data:

$$Abs\_CAR[-1, 5] / Turnover[-1, 5] = \alpha + \beta_1 T_i + \sum \beta_n Controls_{i,t} + FE + \varepsilon_{i,t}$$

In this estimation, the dependent variable *Turnover [-1, 5]* is the cumulative turnover ratio, which equals the ratio of the number of shares traded during the windows to the number of shares outstanding; and *Abs_CAR[-1, 5]* is the absolute value of cumulated abnormal returns in the window [-1, 5], where abnormal returns are calculated as raw returns less the market returns on the same day. *Ti* represents the firm's randomly assigned treatment group. Control variables, industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. *t-stat*istics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Turnover [-1, 5]		Abs_CAR[-1, 5]	
	(1)	(2)	(3)	(4)
Treat	0.021*		0.004	
	(1.91)		(0.71)	
Summary		0.045**		0.012**
		(2.67)		(2.44)
Summary & Sentiment Label		-0.003		-0.003
		(-0.20)		(-0.33)
Controls	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
# of Observations	1,105	1,105	1,105	1,105
R-squared	0.01	0.24	0.14	0.04

Panel B: Conditional on the number of questions

This table reports the OLS regression results from estimating the following model using firm-level data. We partition the sample into terciles based on the number of questions raised in a certain conference:

$$Abs\_CAR[-1, 5] = \alpha + \beta_1 Treat_t + \sum \beta_n Controls_{i,t} + FE + \varepsilon_{i,t}$$

In this estimation, the dependent variable *Abs_CAR[-1, 5]* is the absolute value of cumulated abnormal returns in the window [-1, 5], where abnormal returns are calculated as raw returns less the market returns on the same day. *Ti* represents the firm's randomly assigned treatment group. Control variables, industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. *t-stat*istics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Abs_CAR[-1, 5]		
	(1)	(2)	(3)
	Highest	Medium	Lowest
Treat	0.015***	-0.004	0.004
	(3.37)	(-0.51)	(0.19)

Controls	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes
# of Observations	341	435	329
R-squared	0.08	0.08	0.08

Panel C: Investor Interaction Platform

This table reports the OLS regression results from estimating the following model using firm-level data:

$$\text{Ratio (Posts [0,30]/ Posts [-90, -1])} = \alpha + \beta_1 \text{ Treat}_t + \sum \beta_n \text{ Controls}_{i,t} + \text{FE} + \varepsilon_{i,t}$$

In this estimation, the dependent variable, Posts [0,30]/ Posts [-90, -1], is defined as the ratio of posts from investors on the investor interaction platforms (EasyIR for the Shenzhen Stock Exchange and ehudong for the Shanghai Stock Exchange) within the period [0,30] to posts during the period [-90, -1]. We use this variable to measure the change in investor activity. The event day is the date of the conference call. *Ti* represents the firm's randomly assigned treatment group. Control variables, industry FEs, province FEs, and day FEs are included in all columns. Standard errors are clustered by industry. *t-stat*istics are reported in parentheses ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Posts [0,30]/ Posts [-90, -1]		Posts [0,90]/ Posts [-90, -1]	
	(1)	(2)	(3)	(4)
Treat	0.061***		0.090	
	(3.34)		(0.93)	
Summary		0.072***		0.126
		(5.75)		(1.20)
Summary & Sentiment Label		0.049		0.056
		(1.48)		(0.60)
Controls	Yes	Yes	Yes	Yes
Industry FE, Province FE, and Day FE	Yes	Yes	Yes	Yes
# of Observations	942	942	942	942
R-squared	0.131	0.131	0.105	0.106

Figure 1: Example of a Conference Call Page

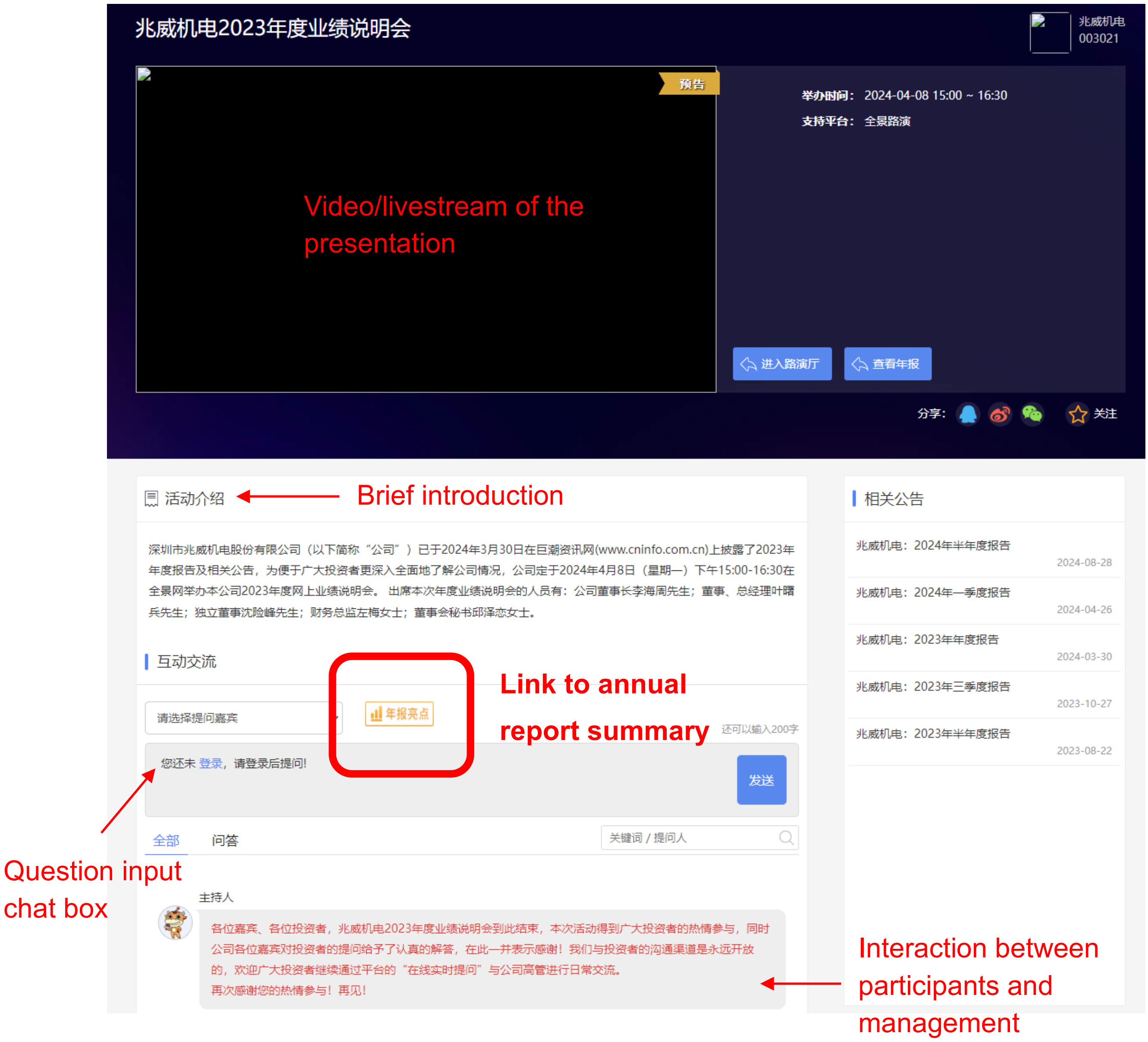

Figure 2: An Example of an AI-generated Summary

a. Treatment: Summary Only

b. Treatment: Summary & Sentiment

Appendix A: Sample Summaries (Translated)

Panel A: A Sample Summary

1. Company Overview and Main Business

Shandong Chenming Paper Group Co., Ltd. is a limited liability company located in Shouguang City, Shandong Province, China. Originally known as Shouguang County Paper Mill, it has undergone several reorganizations and shareholding system reforms to become a large-scale company primarily engaged in the production of machine-made paper and paperboard. The company's main business activities include the production and sales of machine-made paper, electricity and thermal power, building materials, and papermaking chemical products. Additionally, the company is involved in forestry cultivation, seedling breeding, and processing and sales of timber and building materials, as well as hotel services, equipment financing leases, and other fields.

2. Financial Status

According to the 2023 annual report, the company is facing certain financial pressures. During the reporting period, the company achieved a revenue of 26,608,570,228.20 yuan, a decrease of 16.86% compared to the previous year; the net profit attributable to shareholders of the listed company was -1,281,289,649.82 yuan, indicating a loss. The company's total assets were 79,847,052,953.58 yuan, with total liabilities of 58,389,197,107.95 yuan and a debt ratio of 73.6%, showing that the enterprise has a certain financial pressure.

3. Research and Innovation

The company places great emphasis on technology research and development as well as innovation. During the reporting period, it applied for 33 patents and obtained 42 authorized patents, reflecting continuous investment in technological innovation and achievements. Through continuous technological improvements and product innovation, the company aims to enhance product quality and market competitiveness, laying the foundation for long-term development.

4. Market and Sales

The company's products are mainly sold in the Chinese mainland and overseas markets, with the machine-made paper business being the main source of the company's revenue. The company strives to expand the market and improve sales efficiency by establishing a sales network, implementing sales strategies, and optimizing customer service. However, during the reporting period, due to downstream demand and raw material price fluctuations, the company's sales revenue declined.

5. Environment and Social Responsibility

The company actively fulfills its environmental protection responsibilities, adhering to the concept of “green development and environment first,” and invests heavily in the construction of environmental protection facilities, such as alkali recovery systems and water reuse systems, to reduce environmental pollution in the production process. At the same time, the company also focuses on social responsibility, giving back to society through various public welfare activities, such as contributing to the “Good Quality Shandong” brand, enhancing the brand image.

Panel B: A Sample of Summary & Sentiment

1. Company's Potential Risks [Negative]

Financial Status and Profitability: Zhejiang Boyuan Electrical Co., Ltd., reported a revenue of 311,609,137.40 yuan for the year 2023, marking an 11.86% decrease from the previous year's 353,531,847.22 yuan. The net profit attributable to shareholders of the listed company was 32,990,152.49 yuan, a significant 52.40% decrease from 69,302,747.72 yuan in 2022. The basic earnings per share decreased from 1.07 yuan in 2022 to 0.41 yuan, a decline of 61.68%. However, the net cash flow from operating activities improved to a positive 25,956,925.88 yuan, a substantial increase of 197.37% from the previous year.

2. Company's Steady Development [Neutral]

Dividend Plan and Capital Situation: The company's board of directors has approved a profit distribution plan, which proposes to distribute a cash dividend of 0.86 yuan per 10 shares (before tax) to all shareholders based on the total share capital excluding repurchased shares at the time of the next profit distribution plan implementation. The company has a total share capital of 80,000,000 shares and a registered capital of 80,000,000.00 yuan as of the end of the reporting period.

3. Company's Future Growth [Positive]

Main Business and Market Layout: The company's main business focuses on the research and development, production, and sales of electrical insulating materials and other polymer composites. Its products include insulating resins, slot wedges, and laminated products, fiber products, mica products, and binding products, which are used in various fields such as wind power generation, rail transit, industrial motors, household appliances, new energy vehicles, and hydroelectric power. The company has a stable market presence in China and is actively expanding into international markets.

4. Company's Future Growth [Positive]

R&D Investment and Technological Innovation: The company places a high priority on R&D investment, with a 2023 R&D expense of 25,108,088.78 yuan, a 5.71% increase from 23,751,502.28 yuan in 2022. It holds 101 invention patents and 25 utility model patents, has participated in the drafting of multiple national, industry, and group standards, and has undertaken key national and provincial scientific research projects.

5. Company's Steady Development [Neutral]

Risk Factors and Response Measures: The company faces risks such as high customer concentration, safety production risks, potential uncollectible accounts receivable, and raw material price volatility. To mitigate these risks, the company plans to adopt measures such as diversifying market layouts, strengthening safety production management, optimizing accounts receivable management, and procurement strategies to reduce the impact of potential risks.

Appendix B: Examples of Investors' questions in each dimension of Bloom's taxonomy

Dimension	Example
Remembering	What is the company's investment in R&D expenses? How many technical personnel does the company employ?
Understanding	I'd like to inquire about the current canning rate of ABC. Could you share what level it's at? Additionally, does the company's canned product line yield higher gross margins compared to bottled products?
Applying	At the rubber and plastics exhibition, we noticed your company offers numerous product application solutions for industries like sports equipment and medical devices. Beyond the automotive and home appliance sectors, in which other industries has your company recently achieved significant business growth?
Analyzing	In 2023, the company reported a total profit of 1.346 billion yuan, while the net profit was 1.084 billion yuan. What are the primary factors contributing to the difference between these two figures? Were there any significant impacts from non-recurring gain or loss items on the net profit?
Evaluating	The company has made significant investments in the smart energy sector, particularly in virtual power plants and multi-resource coordinated frequency regulation technologies. How will these technologies reshape the company's role in future electricity markets? Does the company plan to commercialize these solutions and offer them as services to create new revenue streams?
Creating	Given the company's substantial investment in R&D during 2023 and the successful filing of multiple patents—with invention patents representing a significant portion—could you elaborate on how the company plans to leverage these technological innovations to drive business growth? Additionally, what specific market opportunities does the company aim to capitalize on through these achievements?