Setting the Right Tone: How Data Science Enables Investor Communication to Choose the Right Language

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Abstract. Facts matter in financial communication, but academic research has revealed that soft information such as the tone and readability also impact the decision-making of investors and ultimately stock returns. Information Systems (IS) research has developed measures to quantify readability and tone of textual content, among which are techniques from statistical learning which are capable of extracting the most relevant words for investors. To make this knowledge accessible, we develop an IS prototype that guides communication practitioners to set the right tone in their investor communication. First, we identify relevant practitioner needs using requirements engineering. Second, we translate these needs into an IS prototype which seamlessly integrates into text editing processes and serves as a decision support system to steer readability and tone. Third, we pilot our IS prototype with 37 companies and successfully validate our prototype's capabilities in a survey with financial professionals.

Keywords: Decision Support Systems (DSS), Information Processing, Investor Communication, IS Prototype, Sentiment Analysis

1 Introduction

Financial markets are facing ever increasing information flows [1], [1]. On the one hand, this burgeoning data volume enables analysts to make more educated judgments on valuation and, thus, allows investors to make better informed investment decisions. On the other hand, the sheer amount of available information can be overwhelming for both individuals and companies [1], [1, 3]. Consequently, this inevitably calls for decision support systems in financial markets. Such decision support systems should be directed at all stakeholders involved in the dissemination of information in financial markets. By that, these systems should assist both senders of information (e.g. investor relations departments within companies, financial news agencies) and recipients of relevant information, such as financial analysts and investors [4], [5]. In fact, the latter group, i.e. investors as recipients of relevant information, already relies to a large extent on decision support systems. Examples include forecasting systems, text mining software and trading algorithms which support or improve decision-making.

The aforementioned systems partially originate from Information Systems (IS) research. IS research has made significant contributions to develop decision support systems for financial markets, especially for investors [6]. However, this is in contrast to the sending-side of relevant information for financial markets, typically investor relations departments.[1] This group typically lacks customized systems to support the process of preparing financial disclosures. Thus, they cannot rely on such a variety of decision support systems in order to tailor their news flow to the changing needs of capital markets [1].

Academic research has identified two key criteria characterizing high-quality investor communication: a positive tone and a high text readability [7–9]. In fact, many IS studies focus on the relationship between investors and textual information. Most of this research evaluates the tone of language in written communication as an indicator for its impact on investors [6], [9], [10]. Speaking broadly, one can refer to this tone of messages as *sentiment* which is a popular research topic in IS. However, as our understanding of tone of language in a financial market includes more than just the sentiment, namely the impact of language on the stock market, we refer to it as *tonality analysis* in the following. In contrast to sentiment analysis, our approach algorithmically computes the (positive or negative) perception of words to support authors in enhancing the tone. Needless to say, tonality and sentiment analysis are closely related, while the underlying methods can vary considerably [11].

In addition to a positive tonality, academic research reveals that companies must also communicate their messages clearly and concisely in order to reach investor attention. To measure the efficiency of information transmission in messages, readability measures are the quantitative lever of choice [8], [7].

This paper fills the gap of a lacking decision support systems for issuers of financial disclosures. Evidence-based support systems are of high practical value for corporate communication executives to facilitate, e.g. investor communication. This paper therefore suggests an IS prototype which builds on academic knowledge in the area of tonality and readability analysis for capital market communication. Accordingly, our IS prototype works as a decision support system that highlights words with a positive or negative tonality and then provides optional replacements with a better tone for the purpose of improving the readability and tonality of written communication[2]. In order to maximize usability, we pursue a rigorous requirements engineering with potential users prior to programming the IS prototype [12]. Finally, we successfully back-test the enhancements to tonality and readability of our IS prototype in a survey with 66 financial professionals.

The remainder of this paper is organized as follows: Section 2 describes the requirements engineering to identify the user needs. Based on these requirements, Section 3 outlines the textual analysis, while Section 4 describes our user interface

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[1] Investor relations departments are in charge of communicating the performance of a stock-listed company towards financial markets. For investors, the news flow of a company is a highly relevant information source. Thus the way in which companies compose their investor updates, in line with existing regulations, acts as an important driver of share price movements.

[2] Regulatory disclosures must meet specific requirements regarding the content. However, they are typically not regulated in terms of actual word choice.

including available features. In Section 5, we present the results of validating the tonality enhancement of our IS prototype with financial professionals. Section 6 highlights the managerial implications of our IS prototype. Finally, Section 7 concludes and provides a research outlook.

2 Requirements Engineering

The fact that virtually all stock-listed companies have investor relations and corporate communications departments indicates the importance of communicating a company's performance to external stakeholders, including investors. However, practical knowledge of how investors perceive this communication is scarce as interviews with capital market communication practitioners reveal. Building on [12], we conduct a total of 18 semi-structured interviews with investor relations and communications departments of four global pharmaceutical companies headquartered in the UK, the US and Switzerland and with the investor relations associations of Germany, the UK and Austria.

During the semi-structured interviews, we collect unmet needs and requirements and cluster these into similar themes (e.g. integration into existing processes and simple-to-use interface belong to one such cluster). The interviewed practitioners particularly highlight that they currently lack a decision support tool to guide them how to write financial disclosures in line with the increasing automation of language processing by (automated) investors. Overall, we identify six requirement clusters (two non-functional, four functional), including the following two non-functional requirements:

- *(i) Objective fact base of investors' language perception.* To date, practitioners lack an objective fact base of how investors perceive the language in financial disclosures and process it. Yet, academic research shows that the tone of language matters to investors [7–9].
- *(ii) Defense mechanism against algorithmic trading.* The increasing importance of algorithmic trading, accounting for more than half of the market order volume [13], concerns investor relations practitioners. They particularly claim a misbalance with an increase in algorithmic trading based on language cues in financial disclosures [5], [14], while they do not dispose of tools to adapt their communication to automated trading based on the language used in corporate disclosures. Thus, making knowledge on how investors process language accessible would better equip investor relations against algorithmic trading.

In addition, we identify four functional requirements:

- *(iii) Compliance with insider trading law.* To ensure compliance with insider trading laws, the IS prototype must operate securely and reliably such that accessing confidential data is impossible. Hence, the IS prototype may not include any protocol that tracks information contained in a yet-to-be-published stock-

market-relevant announcement. In addition, the tool should maintain its full functionality in the offline mode, e.g. to enable usage during travel.

– *(iv) Simplicity and integration into existing processes.* Practitioners stress the importance of a tool's simplicity and high usability and its seamless integration into existing writing processes. Writing processes shall not become complicated due to yet another tool, but rather be simplified with the help of a user interface that integrates directly into conventional text editors.[3]

– *(v) Collaboration-fostering design.* The process of drafting written corporate communication typically involves several departments (e.g. communications, legal, finance, media). To allow for cross-departmental collaboration, the tool needs to have a self-explanatory reporting dashboard. The dashboard further must be sharable via e-mail or as a PDF.

– *(vi) User-controlled change process.* Corporate disclosures are carefully written based on the available facts, legal requirements and corporate standards. Thus, all changes need to be initiated manually by users, to assure that the IS prototype does not unintentionally modify texts.
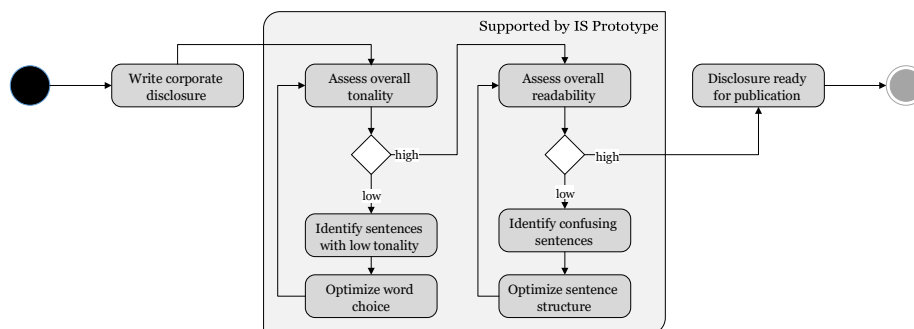

Figure 1. Activity diagram in UML notation showing the reference use case of our IS prototype.

Thus, the IS prototype is intended to support companies in achieving these targets. Moreover, it also incorporates the fact that the editing process of corporate disclosures is highly iterative. The reference use case that serves as the basis to guide our programming efforts and the design of the software system is visualized in a unified modeling language (UML) diagram in Figure 1.[4] As highlighted in the UML diagram, the initial step for companies is to write a first version of the corporate disclosure. Then, the IS prototype helps to assess the overall tonality. In the case of an unsatisfactory tonality, the IS prototype supports users in optimizing their language. In a second step, the IS prototype assesses the overall readability and highlights sentences with

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[3] According to our interviews, the predominant text editor among corporate communications departments is Microsoft Word.

[4] The unified modeling language is a common standard to describe the design of a software system. See [15] for details.

optimization potential in case the readability is unsatisfactory. Once the tonality and readability are at satisfactory levels, the disclosure is ready for publication.

Next, we define the end-to-end process behind the development of our IS prototype (see Figure 2). After deriving the requirements of our IS prototype, we collect and pre-process a database of historic financial news disclosures. Then, we extract words that are statistically relevant to investors [11]. This results in a tailored tonality dictionary that contains positive and negative words with relative weights. Finally, we integrate this dictionary into a text editor that fits into existing writing processes. It is noteworthy that we entirely separate our text analytics from the user interface to bundle all computation-intensive analytics in previous processing steps. This ensures that users immediately obtain the correct tonality and readability scores. In the following sections, we further detail the way we generate tonality dictionaries and measure readability.
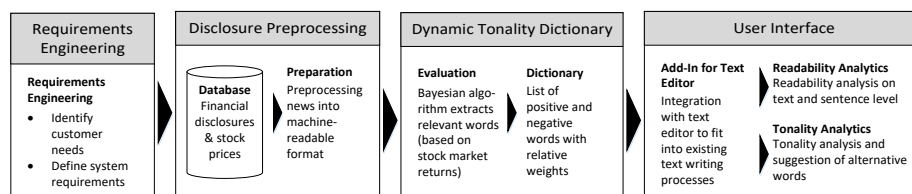
Requirements Engineering	Disclosure Preprocessing	Dynamic Tonality Dictionary	User Interface	
Requirements Engineering • Identify customer needs • Define system requirements	**Database** Financial disclosures & stock prices	**Preparation** Preprocessing news into machine-readable format	**Evaluation** Bayesian algorithm extracts relevant words (based on stock market returns)	**Dictionary** List of positive and negative words with relative weights	**Add-In for Text Editor** Integration with text editor to fit into existing text writing processes	**Readability Analytics** Readability analysis on text and sentence level **Tonality Analytics** Tonality analysis and suggestion of alternative words

Figure 2. The above flow diagram shows the IS prototype development as an end-to-end process.

3 Data Analytics to Enable Evidence-Based Communication

3.1 Tonality Dictionary Generation

While financial sentiment analysis in IS research primarily counts the relative frequency of positive versus negative words based on standard dictionaries [9], [10], [16], tonality analysis identifies only words that have a relevant and causal effect on buy-or-sell decisions of investors. Among others, this *statistical* approach overcomes a methodological weakness of classical sentiment analysis which typically relies on *manually-selected* word lists that are not adjusted to domain-specific particularities.

For this purpose, we rely on a Bayesian learning approach from [11] that generates tailored dictionaries for the financial domain. Consistent with [17], the authors propose the so-called least absolute shrinkage and selection operator (LASSO) that entails several benefits for dictionary generation. First, this method features a variable selection property that filters out non-informative noise terms and thus, allows to pick only decisive variables in a regression model. Furthermore, the LASSO mitigates the issue of multicollinearity as present when estimating via ordinary least squares. Finally, the LASSO solves the problem of overfitting by finding a reasonable trade-off between bias and variance, which occurs if the model complexity is too high [18]. This results in parsimonious and interpretable models that are particularly suited to extract the words that are most relevant to investors.

As shown in Table 1, we utilize the LASSO approach to generate tailored tonality dictionaries for two different markets along with their corresponding disclosure regulations. First, we cover the U. S. market using a dataset of SEC regulated 8-K filings. Second, we employ a corpus of regulated ad hoc announcements written in English to generate an adjusted dictionary for the German market. In both cases, we measure the stock market reaction following the publication of each financial disclosure. Here, we use the common event study methodology that allows to assess the isolated effect of the financial disclosure on the value of a firm [19], [20].

Table 1. Utilized news sources to generate tailored tonality dictionaries for capital market communication.

Focus	Market	Dataset	Benchmark
Capital market communication	U.S. market	61,241 8-K filings from the years 2004 to 2013	Stock market return
Capital market communication	German market	14,463 ad hoc announcements from the years 2004 to 2011	Stock market return

Based on the input data, i.e. the financial disclosures and the stock market returns, the variable selection property of the LASSO chooses a subset of words that are statistically relevant to investors on the stock market. At the same time, non-informative noise terms are automatically discarded. The coefficient estimates of the LASSO then yields an individual tonality score $s_t \in [-\infty, +\infty]$ for each relevant word.

The resulting weighted word lists, i.e. the tonality dictionaries, allow to statistically assess the overall tonality of financial disclosures. For this purpose, we determine the tonality of a document d by calculating the tonality score $T_d = \sum_t s_t f_{t,d}$. Here, the frequencies $f_{t,d}$ describe how often term t occurs in the document d. The tonality metric T_d thus anticipates the market reaction to the language used in this document. In a next step, the dictionary in combination with the tonality metric can be used to enhance the perceived tonality of a document. For instance, one can exchange words with a negative tonality score with more positive replacements.

Compared to the state of the art, the presented statistical approach significantly outperforms frequently-utilized manually selected positive and negative word lists in terms of explanatory power and predictive performance [11]. Moreover, the generated tonality dictionaries are highly adjusted to domain-specific particularities in capital market communication. In contrast to existing dictionaries that postulate, by definition, an equal importance of all included words, the tonality dictionary also reflects a continuous bandwidth of tonality levels. However, the tonality dictionary only contains words which are used in a financial context and are found to have a statistical impact on the stock market price. Very rare words or words that are not generally used in financial language may be marked as neutral even if these may actually have an impact on reader perception.

3.2 Readability Analytics

An extensive body of literature finds that lower levels of readability reduce investors' reactions to news content [8], [7], [21–24]. Since investors face an ongoing and constant flow of new information, an easy-to-read representation of new information is essential to assure that investors can easily extract relevant information from new financial disclosures. Regulatory handbooks, such as the SEC Plain English Handbook [25], guide the editing of financial disclosures to a certain extent. However, the focus of such regulations is on what to communicate and only to a lesser extent on how to communicate the facts leaving significant freedom to communicators.

In order to fulfill the functional requirements of simplicity and a seamless integration into existing processes, we choose the readability metric based on these criteria. We implement the Automated Readability Index (ARI), as defined in [26], [27], to measure the readability of texts evaluated with our IS prototype. The ARI evaluates the readability of a written document by decomposing sentences into two structural components: the number of words in a sentence and the number of characters per word. The ARI is widely used in readability research [28–30]. In detail, the ARI's formula is defined by

$$ARI = 4.71 \, \frac{\text{characters}}{\text{words}} + 0.5 \, \frac{\text{words}}{\text{sentences}} - 21.43. \tag{1}$$

Other approaches, i.e., the Gunning fog index, rely on counting the number of syllables per word. However, this requires higher computational effort and results in a worsened error rate in the computation of the index. Thus, we follow [31] and choose ARI as a superior approach.

The readability information is used by practitioners to identify sentences with especially bad readability and to compare the readability of various documents to each other. Sentences with low readability may then be improved by either shortening the sentence or using shorter words within the sentence. While ARI provides a comprehensive and quick assessment of readability, it fails to assess more subtle dimensions of readability such as the usualness of certain words.

4 User Interface

As a result of our requirements engineering, the IS prototype should seamlessly integrate into the existing writing process to promote user adoption. We have therefore developed an IS prototype as an add-in for a conventional text editor, i.e. Microsoft Word. We select this text editor due to its predominance in corporate communication departments, but our IS prototype could be integrated into any other text editor as well (requirement (iv) in Section 2).
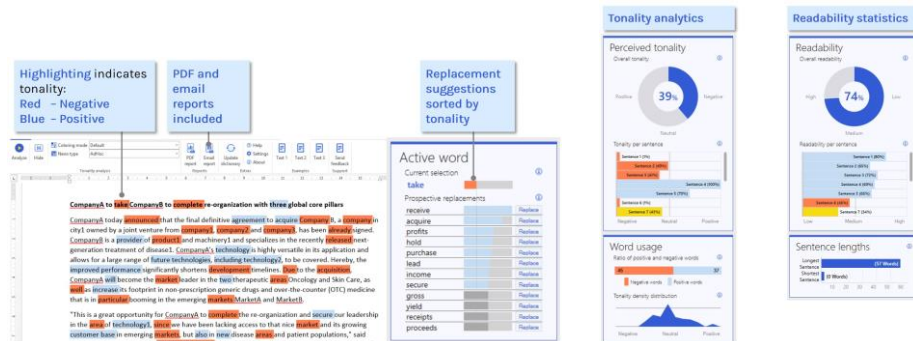
Figure 3. This screen-shot illustrates an exemplary text analysis with our add-in. The word *take*, with a negative tonality, is actively selected by a mouse click. As a result, the active selection panel suggests alternative words, such as the more positive and suitable *acquire*. The center shows the tonality analytics. The right view shows the readability dashboard.

Figure 3 presents our user interface. A drop down menu in the ribbon bar allows users to select a suitable dictionary for the purpose of the underlying communication. For instance, the current implementation of the IS prototype addresses the following domains: (a) a tonality dictionary for capital market communication in the U.S. and the German market following [11], (b) a domain-specific, static dictionary for capital-market communication based on previous research in [16]. This dictionary feature is the core of our application and fulfils the requirements (i) and (ii). The user interface consists of an add-in for a text editor with several functions. As a result of the requirements engineering, the menu (ribbon bar) contains few, but targeted, features. Features include the option to generate a PDF and e-mail report for collaboration (requirement (v)) and a dictionary update function. The dictionary update function allows users to regularly download updated dictionaries from a central server. For this purpose, the add-in automatically communicates with the server and checks for potential dictionary updates. In case updates are available, SSL encryption provides a secure way to transfer the data between server and add-in in line with requirement (iii). To ensure full offline functionality without the need for a continuous internet connection, the dictionaries are encrypted and stored locally after transmission.

Once a suitable dictionary is chosen, users are empowered to objectively analyze the tonality and readability throughout the whole writing process. The tonality analysis highlights words that investors perceive either negatively (highlighted in red) or positively (highlighted in blue). Our IS prototype suggests alternative words as a replacement[5] in case users want to modify the tonality of the underlying document (left

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[5] The replacement function builds on the Thesaurus API of Microsoft Word. We perform a refinement to decide which words to display in the add-in. First, we use a part-of-speech tagger to obtain only context-related words. Then we order the prospective replacements according to their tonality score (from most positive to most negative). In the future, we plan to exclude words that are inappropriate in financial communication, i.e. words that not occur at least once in the financial disclosures corpus.

view of Figure 3). In order to ensure that users retain full control of the textual content, word replacements are never applied to the document automatically. Thus, users are required to manually decide whether individual suggestions are adequate and semantically meaningful. This also implies that users are still fully responsible to comply with the regulatory requirements as requested by requirement (vi).

An analytical dashboard displays the aggregated results of the overall tonality (Figure 3, center) and readability (Figure 3, right). The dashboard further reports the tonality and readability of each sentence to simplify the identification of text parts with a particular tonality or readability improvement potential. The dashboard is equipped with full interactivity. As such, a click on a sentence in the vertical bar diagrams lets the editor jump to the corresponding position and highlights the corresponding sentence in yellow color. In addition, we show a density estimation of the tonality scores t_i. A user can easily interpret this plot and verify if the content matches the actual polarity of the content. For instance, one can avoid the case where negative words describe positive information – by that threatening financial markets where readers and automated traders might interpret the information in a wrong way.

To validate and fine-tune our IS prototype, we collect feedback from demo users. The demo users are 49 investor relations and corporate communications professionals from 37 different companies.[6] We provided each demo user with a 2-minutes video tutorial to explain how the IS prototype may be used. We collected feedback on the installation, usability and benefits via a structured online survey. The results of the survey served to fine-tune the IS prototype.

5   Validation of the IS Prototype Through an Expert Study

One recurring concern of corporate communication professionals regarding our data-driven approach is the real-world validity of our algorithmically derived tonality and readability metrics. We encountered skepticism in various conversations with demo users of our IS prototype, despite that fact that we calculate our tonality dictionaries based on real world financial news. Furthermore, the algorithms only include words in the tonality dictionary which have a statistically significant impact on stock prices. As we do not only strive for statistical significance of our tonality dictionaries, but also for economic relevance, we back-test the impact of modifying texts based on our tonality algorithm and readability index with the typical audience of such communications.

We design a survey to gauge the tonality response of financial professionals to stock-market relevant news. The survey consists of eight questions, which cover some of the most frequent topics in financial disclosures [32], such as earnings reports or acquisition activities. In each question, we show an original extract of a published, regulatory filing

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[6] The 49 demo users are 18 investor relations officers, 12 investor relations advisors (e.g. from financial communication agencies), 5 heads of investor relations, 4 business translators, 3 heads of media relations and communications, 2 capital market legal advisors, 2 consultants, 1 chief finance officer, 1 investor relations journalist and 1 investment fund manager.

published by stock-listed companies. We keep the original extract in its published form and only disguise the name of the respective company.

Seven questions validate the tonality metric, one question validates the readability metric. Among the seven tonality-related questions, five questions relate to text extracts with negative factual content and two questions relate to text extracts with a positive factual content. In each question, we alter either the tonality or the readability based on our tonality dictionary (cf. Section 3.1) and the ARI readability score (cf. Section 3.2). Thus, for each of the eight questions, we have a pair consisting of the original text extract and a text extract in which we enhance the tonality or readability with the user interface. [7] We ensure that the example remains semantically unchanged. As the thesaurus contains also semantically deviating replacement suggestions, the interface requires the active validation of the replacements by the user.

We conducted the survey among financial professionals between February 3, 2016 and April 4, 2016 in collaboration with a corporate communications service provider. We sent the survey link to more than 4,100 analysts and financial professionals by e-mail. In total, 70 financial professionals participated in the survey of which 66 completed the survey. [8] Across our eight questions, we collect a total of 511 observations, thereof 448 observations for the seven tonality-related questions and 63 observations for the readability-related question. The 66 participants left 17 (out of a total 528) questions unanswered. Overall, the results of the back-testing provide strong evidence for the practical validity of the tonality algorithm and the readability statistics used in the IS prototype.

Finding 1: *Financial professionals evaluate tonality-altered disclosures more positively.* In 70.8 (29.2) percent of the observations, survey participants provide a more favorable 'buy-' or 'sell-'recommendation for the tonality-altered (original) disclosure. This provides strong evidence that the tonality enhancement leads to a more favorable recommendation by financial professionals at a statistically significant level (*t*-statistics 6.064; *P*-Value < 0.001).

Finding 2: *Financial professionals are more sensitive to a better tone in negative than in positive news.* A more detailed analysis reveals that financial professionals react more sensitive to the negative tone in a disclosure with a negative underlying factual news content ('sell' recommendation case) than to the positive tone in a disclosure with positive underlying factual news content ('buy' recommendation case). For the five disclosures with a negative factual content, 76.0 (24.0) percent of the survey participants associate a stronger (weaker) 'Sell' recommendation with the original (tonality-altered) disclosure (*t*-statistics 10.897; *P*-Value < 0.001). For the two disclosures with a positive factual content, 57.5 (42.5) percent of the survey

[7] For negative factual news, we ask *Please select the statement that you associate with a stronger sell recommendation (contains information that is perceived as more negative).* For positive factual news, we ask *Please select the statement that you associate with a stronger buy recommendation (contains information that is perceived as more positive).* For readability, we provide the following question *Please select the statement perceived as easier to read.*

[8] Among the 66 participants, 11 are buy- or sell-side analysts, 7 in investment banking, 5 in communications, 13 in consulting and 30 in other finance-related areas, e.g. advisory. Participants could enter a draw of two Amazon vouchers worth 25 euros each.

participants associate a stronger (weaker) 'buy' recommendation with the tonality-altered (original) disclosure (*t*-statistics 1.698; *P*-Value < 0.05). This suggests that the effect of a more positive tone is stronger in negative disclosures. This finding is in line with the psychological negativity bias, which stipulates that human agents weigh negative stimuli more than positive stimuli [33], [34]. Thus, according to the negativity bias, negative information is weighted more heavily than positive information [35].

Finding 3: *Financial professionals rate the readability-altered disclosure as easier to read.* 77.8 percent of the survey participants rate the readability-altered disclosure as easier to read at a statistically significant level (*t*-statistics 5.261; *P*-Value < 0.001).

Table 2. Original and tonality- and readability-altered text pairs of back-testing validation survey (tonality-manipulated words highlighted in bold).

Focus	Original text extract	Altered text extract
Tonality (neg. factual content)	For the full year 2015, we now **expect** somewhat **weaker** growth for the global economy as well as global industrial and chemical production than was **forecasted** six months ago.	For the full year 2015, we now **anticipate** somewhat **retarded** growth for the global economy as well as global industrial and chemical production than was **predicted** six months ago.
Tonality (neg. factual content)	The oil price-related **decrease** in the Oil & Gas segment **dampened** earnings, while the Functional Materials & Solutions and Chemicals segments provided support through greater contributions.	The Functional Materials & Solutions and Chemicals segments provided support through greater contributions, while the oil price-related **headwinds** in the Oil & Gas segment **compromised** earnings.
Tonality (neg. factual content)	**Contrary** to the general market **expectation**, steel prices **continued to decline**, mainly **due to** a **further** decrease in quotations for Chinese steel exports.	**Different** to the general market **consensus**, steel prices **further fell**, mainly **caused by** an **additional** decrease in quotations for Chinese steel exports.
Tonality (neg. factual content)	The Q3 earnings before interest and taxes (EBIT) of approx. EUR 30 million **turned out significantly weaker than anticipated**.	The Q3 earnings before interest and taxes (EBIT) of approx. EUR 30 million **were behind plan**.
Tonality (neg. factual content)	The company said Thursday that currency fluctuations will **reduce** full-year profit by 85 million pounds, trimming an earlier **forecast** of 100 mio.	The company said Thursday that currency fluctuations will **lower** full-year profit by 85 million pounds, trimming an earlier **prediction** of 100 mio.
Tonality (pos. factual content)	Brew Co. **reported** a better-than-**expected** 7 percent **rise** in underlying third-quarter sales on Thursday, **helped by gains** in Africa and South America, and stronger growth in Europe, where unseasonably mild weather boosted demand.	Brew Co. **published** a better-than-**anticipated** 7 percent **increase** in underlying third-quarter sales on Thursday. **Gains** in Africa and South America, and stronger growth in Europe, where mild weather boosted demand, **stimulated the sales increase**.
Tonality (pos. factual content)	**Following** the transaction, UBM **expects** to **maintain** its investment grade status with the credit rating agencies.	**Succeeding** the transaction, UBM **anticipates** to **confirm** its investment grade status with the credit rating agencies.
Readability	This will be aggravated by losses of sales that are now expected and the consequently missing earnings contributions: the Company's business prospects are being affected by the worsened economic conditions in China and Russia, which will probably lead to reduced demand, while U.S. business with the commercial vehicle industry as well as the amount of sales to some customers will likely not be at the previously budgeted level	This will be increased by reductions of sales that are now anticipated and the resulting lower earnings contributions. The Company's business prospects are being affected by the impaired economic conditions in China and Russia, which will probably lead to lessened demand. The U.S. business with the commercial vehicle industry as well as the amount of sales to some customers will likely not be at the previously budgeted level.

Overall, the findings provide supportive evidence for the practical validity of our algorithm-based decision support system for capital market communication. One limitation of our approach is the low number of observations.

6   Managerial Implications

Our IS prototype offers several managerial implications for corporate communication executives. In particular, we have identified three particularly relevant managerial implications:

Implication 1: *Practitioner-friendly tonality analysis.* While current state-of-the-art tonality analysis requires in-depth methodological knowledge as well as advanced analytical skills, the proposed add-in enables any communications practitioner to perform state-of-the-art tonality analysis of disclosures before publication. The add-in thus gives practitioners an information advantage as the perception of texts by investors is forecasted immediately. Furthermore, practitioners are supported with replacement suggestions to improve the tonality and a holistic readability assessment.

Implication 2: *Quality compliance check.* Our IS prototype facilitates a natural compliance check in the writing process as overly negative or positive language is immediately flagged by the tonality assessment. Similarly, issues in the readability become visible when checking the readability metrics of a text. While regulatory frameworks, e.g. the SEC disclosure regulation, provide clear guidance on the content of stock-market-relevant announcements, they only give little guidance on how to write disclosures beyond using plain language [22] [25], [36]. Furthermore, a study of KPMG among investment professionals [1] finds that existing initiatives, such as the SEC Plain English Handbook, have an almost negligible impact in current industry practice. In fact, only 19 percent of the study participants report a positive impact of the plain English initiative on facilitating the disclosure process. In that context, our IS prototype could serve practitioners as a compliance check against regulatory frameworks and support practitioners in putting such regulatory frameworks into practice.

Implication 3: *Process efficiency gains.* The IS prototype integrates directly into conventional text writing processes and offers an objective assessment of the readability and tonality of texts. These assessment results can be easily shared with team members or other departments via the reporting features. Thus, the IS prototype contributes to accelerate the text writing process, especially in settings with multiple stakeholders (e.g. media relations, investor relations, legal, top management). In one interview, we have learned that disclosures of less than 400 words sometimes involve more than 100 iterations. Our tool addresses this process inefficiency by structuring discussions around individual word choices and the overall tone and readability that a company now can deliberately choose in its communication.

In addition, anecdotal evidence from pilot users of the IS prototype confirms the above implications 1 and 3. The director of investor relations at a UK-based pharmaceutical company shares his early user experience in an investor relations professional journal [37]: *"The add-in equips us with deep knowledge on the anticipated reaction of investors. We can now replace subjective feelings by actual evidence when discussing different wording for the very same story"*.

The overall contribution of this IS prototype is twofold: first, we open new avenues for making IS research accessible to practitioners. As such, the prototype serves as a statistically-validated tool to improve form and style of written corporate communication. Second, based on a collaborative approach, the insights and knowledge generated by the practitioners shall flow back to academia, which may then draw conclusions regarding the economics and value of IS on the usage of such a decision support system in practice.

7 Conclusion

In order to successfully compete for investor attention in light of ever-increasing information flows, companies need to ensure that their written communication conveys the relevant information in an easy-to-read manner. Previous research has identified readability and the tone of language as two key elements of successful and positive communication. However, as interviews with investor relations practitioners show, practical tools to steer the investor-specific tone and readability in capital markets communications are not yet available.

The results of the study suggest that improving the tonality of disclosures on basis of the tonality dictionaries leads to significantly more favorable evaluations of the disclosures by financial professionals. In summary, the prototype is a decision support system that not only describes and analyzes data, but directly suggests improvements to users to enhance the tone and readability whilst preparing financial market communication.

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