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APPLYING TEXT MINING FOR EVIDENCE-BASED POLICY: SENTIMENT AND TOPIC ANALYSIS OF INDONESIA'S RESEARCH FUNDING REFORM

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ABSTRACT

A substantial portion of governance-relevant information in Indonesia is contained in unstructured textual artefacts such as meeting minutes and focus group discussion (FGD) notes, yet these materials remain underutilized in policy evaluation. Existing studies have not systematically examined how computational text analysis can extract policy insights from such documents. The purpose of this research is to evaluate the implementation dynamics of the RIIM funding scheme during its transition to SBK, and to generate evidence-based recommendations that support the development of a more adaptive and context-sensitive research funding framework. This study employs a text-mining approach combining exploratory word cloud visualization, lexicon-based sentiment analysis using the Bing lexicon, emotion analysis using the NRC Emotion Lexicon, and Latent Dirichlet Allocation (LDA) topic modeling. The analysis is conducted on a corpus derived from Focus Group Discussion (FGD) verbatim transcripts involving RIIM stakeholders, consisting of 13 pages and 4,188 words. The findings reveal four major issue clusters: administrative and contractual inconsistencies, ambiguity in output classification across research fields, uncertainty in financial and temporal transitions, and challenges in aligning performance evaluation with diverse research outputs. These findings inform concrete recommendations for enhancing procedural clarity, establishing explicit transitional provisions, strengthening output classification, and institutionalizing stakeholder feedback mechanisms. This study acknowledges limitations related to the use of English-based sentiment lexicons for Indonesian data and the reliance on summarized minutes rather than verbatim transcripts. The study's originality lies in demonstrating how computational text analysis can systematically extract policy insights from unstructured governance documents, offering a novel evidence-based approach for refining Indonesia's research funding instruments.

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1. INTRODUCTION

Indonesia's post-2019 research funding framework remains constrained by insufficient performance-evaluation mechanisms and the limited adaptability of funding instruments to the heterogeneous conditions and operational realities faced by researchers nationwide. These persistent gaps highlight the need for continued policy reforms aimed at strengthening accountability and regulatory coherence, thereby enabling funding schemes to more effectively align with researcher needs while simultaneously advancing the government's broader national development objectives [1]. This aligns with the findings of previous research, which shows that the efficiency of research funding schemes is strongly dependent on the degree of alignment between policy instruments and the institutional capacities, as well as the operational contexts of funding recipients [2]. In this regard, understanding the structural and contextual realities faced by researchers and research-performing organizations becomes an implicit yet essential prerequisite for ensuring that funding mechanisms function effectively within diverse innovation ecosystems.

In response to the mandate of Law of the Republic of Indonesia No. 11/2019, the National Research and Innovation Agency (BRIN) introduced the Riset dan Inovasi untuk Indonesia Maju Kompetisi (RIIM) scheme as one of the country's national research funding instruments, designed to strengthen the research ecosystem by improving scientific productivity, researcher capability, and talent development [3]. The scheme was introduced through the Decision of the Deputy for Research and Innovation Facilitation of the National Research and Innovation Agency Number 57/II.7/HK/2025 concerning the Guidelines for Riset dan Inovasi untuk Indonesia Maju Kompetisi (RIIM) [4]. Designed to support knowledge creation and technology development at Technology Readiness Levels (TRL) 3 to 6, RIIM enables doctoral graduates, especially those who studied abroad, to continue their research, transfer expertise, and collaborate across research centers in Indonesia. However, the recent directive from the Head of BRIN (2021–2025 period) to align the RIIM scheme with the Standar Biaya Keluaran (SBK), a performance-based budgeting mechanism that standardizes research outputs and their associated costs, has generated uncertainty among researchers and program managers regarding funding flexibility, implementation timelines, reporting requirements, and the compatibility between planned research outputs and SBK's more rigid categories.

These uncertainties underscore the need for a more systematic policy evaluation to understand how Indonesia's research funding reforms are being interpreted and experienced by actors within the research ecosystem. Conventional evaluation practices rely heavily on formal reports and expert interpretations, which often fail to reflect the complex, distributed, and sometimes conflicting perspectives embedded within the research ecosystem [5]. In line with the logic of contemporary policy analysis, as articulated by Dunn (2017), robust policymaking requires the systematic transformation of diverse information sources, including textual, experiential, and contextual evidence, into actionable knowledge that can illuminate policy problems, clarify stakeholder preferences, and guide appropriate interventions [6].

A substantial share of information relevant to governance in Indonesia is embedded in unstructured textual artefacts such as meeting minutes, focus group discussions, and inter-institutional correspondence [7] [8], yet these materials have rarely been examined through rigorous empirical techniques. Employing text-mining approaches such as sentiment analysis and topic modeling, therefore, aligns with Dunn's conception of evidence-based policy analysis by enabling the extraction of patterned insights, surfacing latent concerns, and revealing areas of policy and practice misalignment that are not captured through traditional evaluative mechanisms [9]. Previous studies primarily examine public perceptions and media discourse on policy issues using social or online textual data, including environmental, health, and crisis-related policies (Table 1).

Table 1. Comparison of Previous Studies

No.	Title	Source Data	Method	Main Focus
1	From tweets to trends: Modeling public opinion for	Twitter (X) data	NLP, sentiment analysis, trend modeling	Understanding public opinion trends to inform policy decisions on

No.	Title	Source Data	Method	Main Focus
	policy insights on emerging technologies [10]			emerging technologies and innovation governance
2	Harnessing public sentiment discourse for early drought detection and water crisis response for strategic water management and resilient policy planning [11]	Social media discourse (multi-platform)	Sentiment analysis, discourse analysis	Using public sentiment signals as early indicators to support proactive water governance and crisis-responsive policy planning
3	Policy feedback in crowd-safety crises: a dynamic topic modeling approach to South Korea's Post-Itaewon crisis [12]	Naver Blog (Korea)	Dynamic Topic Modeling	Analyzing how public discourse evolves and feeds back into policymaking in crisis management and public safety governance
4	Twitter dataset on public sentiments towards biodiversity policy in Indonesia [13]	Twitter (X) (Indonesia)	IndoBERT, Machine Learning	Assessing public perception and acceptance of biodiversity and environmental policies
5	Sentiment Analysis Of Public Opinion On Handling Stunting Using Random Forest [14]	Twitter (X) (Indonesia)	Random Forest	Evaluating public responses to government interventions and policies addressing stunting issues
6	Chinese Public Attitudes and Opinions on Health Policies During Public Health Emergencies: Sentiment and Topic Analysis [15]	Weibo (China)	LDA, BERT, ARIMA	Examining public acceptance, sentiment dynamics, and feedback toward health policy interventions during crises

While these approaches provide valuable insights into public opinion, they remain limited in capturing the perspectives of stakeholders directly involved in policy implementation. Moreover, prior research in policy studies suggests that computational text analysis techniques, such as topic modeling, are effective in identifying textual patterns but have limited capacity to capture contextual meaning, discourse, and stakeholder experiences within policy processes [9]. Therefore, this study utilizes official FGD verbatim transcripts to capture stakeholder experiences in the implementation of research funding policies, enabling a more context-specific and institutionally grounded policy evaluation. Guided by this methodological perspective, this study evaluates the RIIM scheme by analyzing FGD verbatim transcripts generated during consultations conducted by the Directorate of Research and Innovation Funding. Through the application of topic modeling and sentiment analysis to these unstructured textual materials, the study identifies patterned concerns and latent policy misalignments that conventional evaluations often overlook. The resulting evidence supports the formulation of policy recommendations aimed at strengthening the adaptability, coherence, and analytical robustness of Indonesia's future research funding mechanisms.

2. METHODS

Material and Data

The data used in this study consists of the official verbatim transcripts produced during a series of Focus Group Discussions (FGDs) conducted by the Directorate of Research and Innovation Funding with stakeholders involved in the implementation of the RIIM funding scheme. The FGDs were held between 15 October and 27 October 2025 and included 2 Heads of Research Organizations, 20 program and financial managers, and 79 RIIM grant recipients. These discussions were conducted

via virtual Zoom meetings and were formally documented by assigned rapporteurs. All FGD verbatim transcripts were subsequently compiled into a single document in PDF format, resulting in a dataset containing 13 pages and 4,188 words. Although the corpus consists of 4,188 words, it represents a highly curated and policy-relevant dataset derived from structured FGD discussions. In text-as-data approaches, dataset adequacy is determined not only by size but also by information density and contextual relevance [9] [16]. Each FGD was preceded by a brief presentation outlining the government's planned transition toward an SBK-based funding mechanism in 2026; however, the substantive content of the minutes primarily captures stakeholder experiences, challenges, and operational realities associated with RIIM implementation during the 2025 cycle. As such, the dataset provides a rich empirical foundation for evaluating the existing scheme while analytically anticipating policy design issues relevant to the forthcoming SBK reform.

To prepare the dataset for computational analysis, the PDF document was translated from Indonesian into English using Google Translate. Although Indonesian-language NLP resources have become increasingly available, this study adopted an English-based workflow due to several methodological considerations. Many widely used text-mining tools, particularly those employed for topic modeling and sentiment analysis, are more mature, extensively benchmarked, and better integrated within English-language ecosystems, enabling more stable analytical performance and facilitating the integration of multiple techniques within a unified workflow [9]. In addition, the use of widely adopted English-based lexicons and pretrained models, such as the Bing sentiment lexicon and the NRC Emotion Lexicon, ensures consistency and comparability in sentiment and emotion classification across studies. Prior research has also shown that the effectiveness of computational text analysis methods is highly dependent on the alignment between language resources and model assumptions, particularly in topic modeling and text-as-data approaches [16] [17]. Preliminary inspection further indicated that the translated corpus produced more interpretable and stable thematic structures when processed using tools optimized for English. Automated translation ensured uniformity of linguistic structure across the corpus and facilitated the use of text-mining tools, which depend on English-language input for consistent lexical processing. Light preprocessing was applied solely to correct formatting inconsistencies, such as line breaks, duplicated spaces, and non-textual artefacts, without altering the substantive meaning of participant statements to preserve the integrity of participant contributions. This final dataset, consisting of the cleaned and translated transcript of the FGD verbatim transcripts, served as the primary corpus for the sentiment analysis and topic modeling procedures implemented in this study.

Research Method

This study employs a Natural Language Processing (NLP) approach to analyze textual data derived from official verbatim transcripts of FGDs. All analyses were conducted using RStudio Version 2024.09.0+375. The methodological workflow consisted of several key stages: PDF data extraction, data preprocessing and cleaning, and data analysis, such as word frequency analysis and visualization, sentiment and emotion analysis, and topic modelling using Latent Dirichlet Allocation (LDA) [14] [18] [19]. To identify latent thematic structures within the FGD corpus, this study employed Latent Dirichlet Allocation (LDA), a probabilistic topic modelling approach that represents each document as a mixture of latent topics and each topic as a distribution of words. For a corpus consisting of (D) documents and (K) topics, the topic proportion vector for document (d) is assumed to follow a Dirichlet distribution:

$$\theta_d \sim \text{Dirichlet}(\alpha) \quad (1)$$

where:

- θ_d = topic proportion vector for document d
- α = Dirichlet hyperparameter controlling topic sparsity

and that the word distribution of topic k also follows a Dirichlet distribution:

$$\phi_k \sim \text{Dirichlet}(\beta) \quad (2)$$

where:

- ϕ_k = word probability distribution for topic k
- β = Dirichlet hyperparameter controlling word sparsity within topics

For each word n in document d, a latent topic assignment is generated from the document's topic distribution:

$$Z_{dn} \sim \text{Multinomial}(\theta_d) \quad (3)$$

where:

- z_{dn}= latent topic assigned to the n- the word in the document d

and the observed word is subsequently generated from the corresponding topic-word distribution:

$$W_{dn} \sim \text{Multinomial}(\phi_{Zdn}) \quad (4)$$

where:

- w_{dn}= observed word at position n in document d

The probability of observing a word $w$in document d is therefore given by:

$$P(w \mid d) = \sum_{k=1}^{K} P(w \mid z = k)\, P(z = k \mid d) \quad (5)$$

This equation indicates that the probability of a word appearing in a document is computed as the weighted sum of its probabilities across all latent topics, where the weights correspond to the prevalence of each topic within the document. In practical terms, the model estimates the relative contribution of different discussion themes within each FGD transcript and identifies the most representative keywords associated with each latent topic, enabling the extraction of dominant policy issues related to RIIM implementation and the planned transition toward the SBK funding mechanism.

The number of topics (K=4) was determined based on substantive interpretability and the analytical objectives of the study. Given the focused nature of the FGD discussions, four topics were considered sufficient to capture the principal thematic dimensions of the corpus while maintaining conceptual clarity and practical relevance for policy interpretation. Accordingly, statistical model-selection procedures such as coherence score and perplexity evaluation were not applied.

Preprocessing Data

PDF transcripts of the FGD sessions were first imported and converted into raw text using the 'pdftools' package, forming the initial corpus for analysis. To ensure analytical consistency, the text then underwent an extensive preprocessing workflow designed to remove noise and irrelevant elements commonly found in meeting transcripts. This process began with broad text cleaning, including the elimination of non-informative phrases and the application of a custom stopwords list—such as "Machine Translated by Google"—to filter out terms that did not contribute meaningfully to the analysis. The corpus was further refined through several additional preprocessing steps: removing

all custom stopwords, numeric terms, URLs, punctuation-only tokens, and tab characters; excluding words representing dates in common formats (e.g., yyyy-mm-dd, dd/mm/yyyy); and applying whitespace trimming to maintain consistent token structure. Short-word removal was also performed by discarding tokens with fewer than three characters, preventing fragmented or semantically empty terms from entering the dataset. Through this multi-stage and systematic cleaning pipeline, the FGD transcripts were transformed into a coherent and structured corpus suitable for subsequent sentiment analysis, emotion classification, and topic modelling.

Data Analysis

Following the completion of data preprocessing, a series of text mining techniques was applied to systematically analyze the FGD transcripts. Word cloud visualization was used as an exploratory tool to provide an initial overview of term frequency patterns within the corpus. It serves as a descriptive technique to identify prominent words, but does not constitute the primary analytical method. Sentiment scores were derived using the Bing lexicon, which classifies words into positive and negative categories. The overall sentiment was calculated by aggregating the frequency of positive and negative terms within the corpus. Specifically, sentiment polarity was determined as:

$$\text{Sentiment Score} = (\text{Number of Positive Words} - \text{Number of Negative Words}) \quad (6)$$

Similarly, emotion classification was conducted using the NRC Emotion Lexicon, which assigns words to eight emotional categories (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust). The frequency of each category was computed to represent the emotional profile of the corpus. Beyond sentiment and emotion, deeper thematic structures were uncovered through Latent Dirichlet Allocation (LDA) topic modelling. The cleaned corpus was transformed into a Document-Term Matrix, after which LDA was applied to identify latent topics reflecting stakeholder concerns related to funding mechanisms, contractual obligations, administrative barriers, and uncertainties during the transition to an output-based financing system. All analytical procedures were conducted using RStudio with relevant packages, including ‘pdftools’, ‘tidytext’, ‘dplyr’, ‘ggplot2’, ‘wordcloud’, ‘stringr’, ‘tidyr’, ‘tm’, and ‘topicmodels’. This multi-method analytical pipeline provided a comprehensive and statistically grounded foundation for deriving evidence-based policy recommendations.

3. RESULTS

Word Cloud Visualization and Analysis

The word cloud results show that the term “funds” appears most prominently, indicating that this concept is frequently discussed within the FGD transcripts. Other highly frequent terms, such as “contract,” “research,” “million,” “account,” “output,” and “sbk,” further highlight the prevalence of discussions related to funding mechanisms and administrative aspects. The frequent occurrence of terms such as “million” and “output” indicates that these concepts are commonly addressed in the dataset. However, interpretations regarding potential constraints, policy misalignment, or disciplinary differences are derived from the results of sentiment analysis and topic modeling, which provide a more structured basis for analysis.

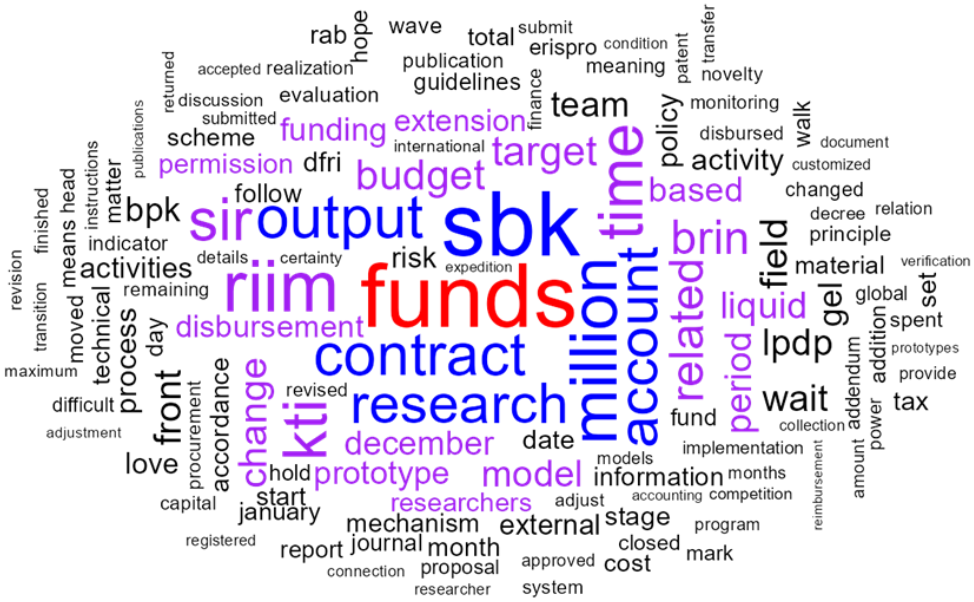

Figure 1. Word Cloud Results

Additional terms such as “permission,” “funding,” “extension,” “budget,” “target,” and “time” point to procedural uncertainty and time constraints experienced by researchers as they adapt ongoing projects to the new SBK framework. Meanwhile, the presence of words like “kti” (scientific paper), “riim,” “prototype,” “model,” and “researcher” illustrates ongoing uncertainty about how non-physical outputs, such as scientific publications, conceptual models, or policy-relevant analyses, can be accommodated within a system traditionally oriented toward more tangible outputs such as prototypes or physical models. Terms including “disbursement,” “period,” and “change” highlight the administrative adjustments and financial transitions that directly affect research implementation on the ground.

These linguistic patterns not only characterize the operational challenges of the 2025 RIIM cycle but also provide early empirical signals of potential misalignment, classification ambiguity, and coordination risks that may intensify once SBK is formally adopted in 2026. By interpreting these 2025 issues as precursors to future implementation dynamics, the analysis underscores how stakeholder concerns during the current cycle foreshadow structural pressures that the SBK reform must address to ensure cross-disciplinary fairness, administrative coherence, and output flexibility.

Sentiment Analysis

The sentiment analysis results show that 100 positive words and 68 negative words were identified within the FGD transcript using the Bing lexicon. This distribution suggests a greater presence of positive-associated terms; however, such frequencies should be interpreted as indicative of lexical patterns rather than a direct measure of overall sentiment.

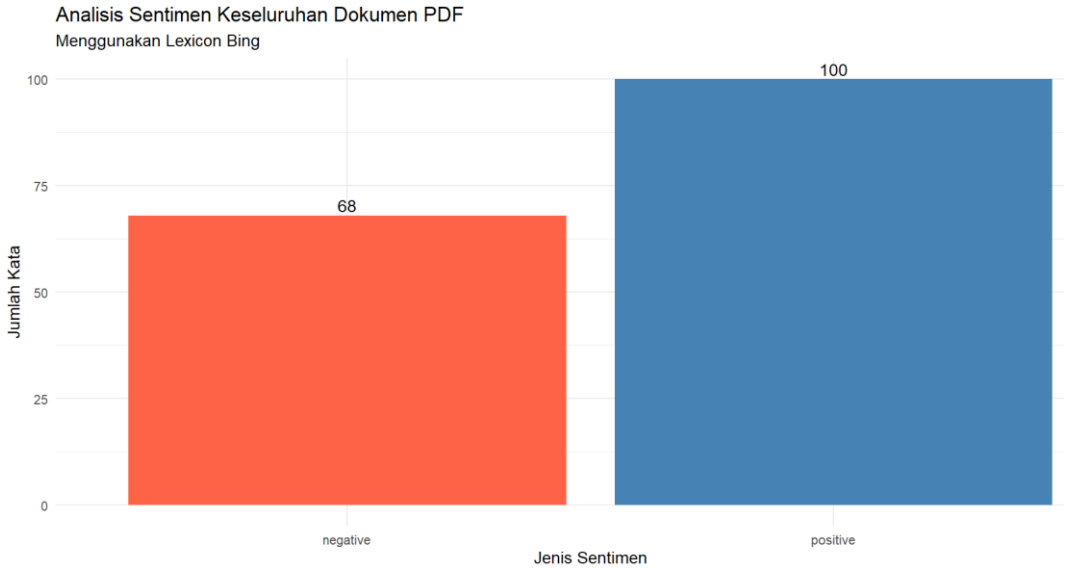

Figure 2. Sentiment Analysis Results

This distribution suggests that, despite extensive discussions on administrative and technical challenges associated with the implementation of the SBK output-based funding mechanism, the general communicative tone remains constructive. Stakeholders appear to frame their concerns through expressions of expectation, requests for clarity, and proposals for improvement rather than through outright complaints or resistance. The presence of negative sentiment terms reflects legitimate concerns regarding policy implementation risks, including uncertainty around disbursement procedures, administrative delays, and potential financial losses associated with end-of-year account closures. Nevertheless, the higher prevalence of positive sentiment terms suggests a shared sense of optimism and collaborative intent among researchers and research managers. Taken together, these 2025 sentiment patterns signal that although operational bottlenecks and rule ambiguities remain pressing concerns, stakeholders demonstrate a baseline readiness to adapt, which becomes a crucial indicator of institutional and researcher preparedness for the planned SBK transition in 2026. Overall, the document reflects a "positive-critical" orientation, acknowledging existing structural issues while maintaining a forward-looking emphasis on solution-building and policy refinement.

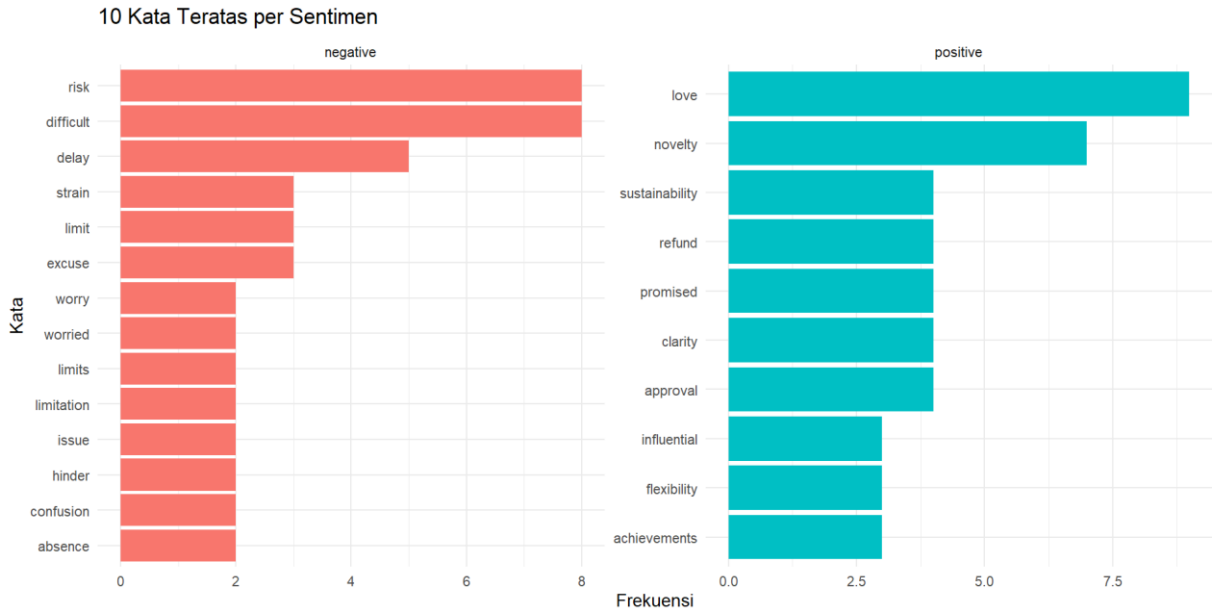

Figure 3. Top 10 Terms for Sentiment Analysis Results

Figure 3 demonstrates consistent differences in the top contributing terms for each sentiment category, resulting in clearly distinguishable thematic patterns. Within the negative sentiment category, dominant terms such as risk, difficult, delay, strain, limit, and worry indicate concerns primarily related to administrative burdens, funding bottlenecks, and constraints perceived to limit research flexibility. Terms such as confusion and absence underscore gaps in information flow and coordination, reinforcing the perception of ambiguity during the transition to SBK. These 2025 expressions of concern highlight not only the operational frictions experienced under the current system but also the potential friction points that may hinder a smooth implementation of SBK in 2026 if left unaddressed. Conversely, the most salient positive terms, such as love, novelty, sustainability, clarity, approval, and flexibility, signal an overarching desire for improvement and adaptation. These terms highlight optimism toward achieving a more transparent and supportive funding environment. Notably, sustainability and flexibility point to expectations that the funding system can evolve to better support diverse research pathways, while clarity and approval reflect the need for strengthened institutional guidance and procedural transparency. This coexistence of critique and constructive aspiration in 2025 indicates that researchers view the SBK transition as feasible, provided the reform addresses core issues related to clarity, administrative consistency, and output flexibility.

Taken together, the sentiment distribution and dominant terms reveal a nuanced narrative: while stakeholders express substantial concern about operational uncertainties and constraints, they simultaneously articulate strong aspirations for innovation, clarity, and adaptability. This combination of critique and constructive intent underscores the importance of refining the SBK mechanism to enhance its responsiveness to the diverse needs of Indonesia's research ecosystem.

Emotion Analysis

The emotion analysis using the NRC Lexicon shows that the FGD transcript is predominantly associated with several high-frequency emotional categories, particularly trust (395 words) and positive (383 words). This distribution indicates a strong presence of trust-related and positive-associated terms within the corpus, reflecting the overall affective composition of the discussion. The emotion category anticipation (194 words) also appears with notable frequency, suggesting that forward-looking expressions are commonly present in the discourse. These linguistic patterns are consistent with discussions related to future policy adjustments, including the need for clearer technical guidelines, enhanced transparency, and greater flexibility in accommodating diverse research outputs. In contrast, the categories negative (128 words) and fear (87 words) represent the occurrence of concern-related expressions, particularly those associated with administrative processes, implementation challenges, and procedural uncertainty. These patterns indicate that both supportive and concern-oriented language coexist within the dataset.

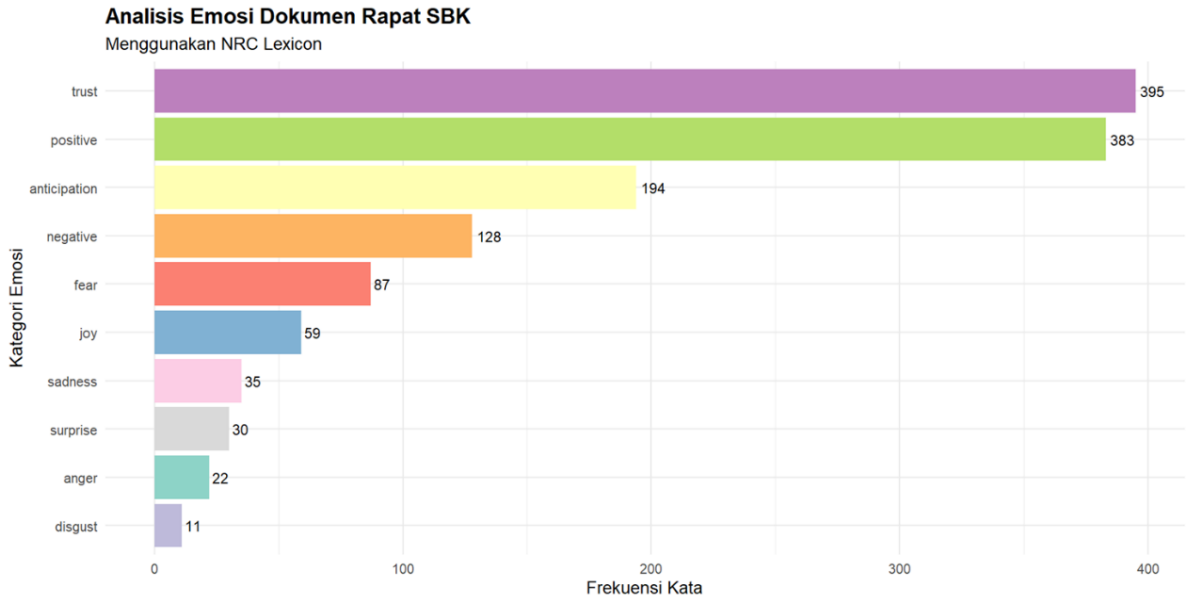

Figure 4. Emotion Analysis Results

Other emotional categories, including joy (59 words), sadness (35 words), and anger (22 words), appear at much lower frequencies, indicating that the discourse did not adopt a highly emotional or confrontational tone. Instead, it remained primarily analytical, evaluative, and solution-oriented. Overall, the emotional profile of the document suggests a balance between trust and caution: while participants voice legitimate concerns about operational challenges, they simultaneously demonstrate confidence and commitment to achieving a research funding system that is more transparent, efficient, and sustainable.

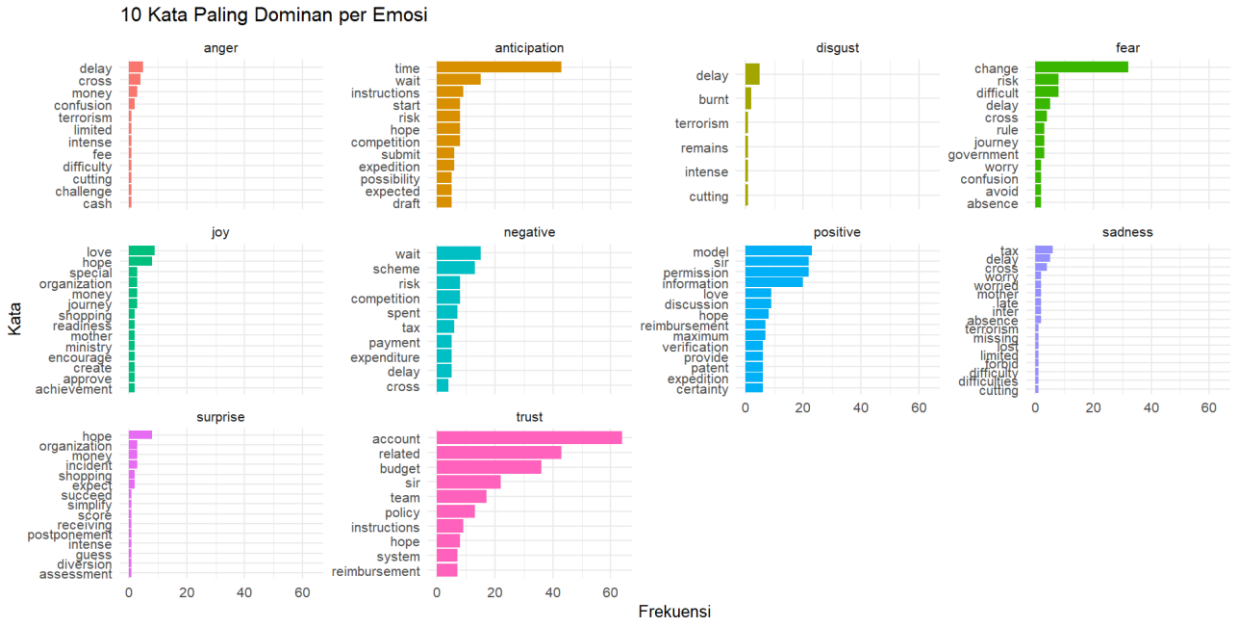

Figure 5. Top 10 Terms per Emotion

The visualization of the top ten keywords for each emotional category (Fig. 5), derived from the NRC Emotion Lexicon, illustrates distinct linguistic patterns associated with the emotional landscape of the SBK policy discussion. These patterns reflect the interplay between concern, expectation, and optimism expressed throughout the FGD transcripts. Trust emerges as the strongest emotional category, with dominant terms such as account, budget, policy, instructions, and reimbursement. The

presence of these terms indicates continued confidence in institutional and procedural mechanisms, suggesting that participants maintain a baseline level of trust in the transparency and accountability of the research funding system, notwithstanding their calls for technical improvements. The emotion anticipation, represented by keywords such as time, wait, hope, and expected, highlights a forward-looking sentiment as participants prepare for ongoing policy adjustments and the operational transition to the SBK mechanism. This sense of expectancy aligns with discussions emphasizing the need for clearer guidelines, timely disbursement processes, and predictable administrative workflows.

Within the positive emotion category, terms such as model, love, hope, clarity, and expedition reflect an underlying optimism and a collective intention to pursue constructive solutions. These expressions signal that the discourse extends beyond critique to include genuine efforts toward adaptation and system enhancement. Conversely, the negative and fear categories, marked by keywords such as risk, difficult, delay, change, and confusion, underscore concerns regarding administrative bottlenecks, procedural uncertainties, and potential disruptions to research continuity under the SBK framework.

Although the sadness and anger categories appear with lower frequency, terms such as tax, lost, confusion, and delay reveal a level of frustration associated with bureaucratic constraints and lost research time. Meanwhile, words linked to joy and surprise, such as love, hope, achievement, and organization, convey a sense of collective pride and satisfaction with existing achievements, paired with curiosity and hope for further improvements. Taken together, these lexical patterns indicate that the emotional climate of the document is predominantly forward-looking and optimistic, tempered by realistic concerns about implementation challenges. The combination of trust and caution expressed by participants contributes to a communication tone that is critical yet constructive, reflecting a shared commitment to strengthening the effectiveness, clarity, and responsiveness of the SBK-based research funding system. Crucially, this emotional configuration suggests that stakeholders' reactions to the SBK transition in 2026 will likely depend on how well the reform addresses the specific operational pain points surfaced through the 2025 data.

Topic Modelling Results

The topic modelling analysis identified four major thematic clusters within the FGD transcripts, each reflecting distinct concerns related to the transition toward the SBK output-based funding mechanism (Fig. 6).

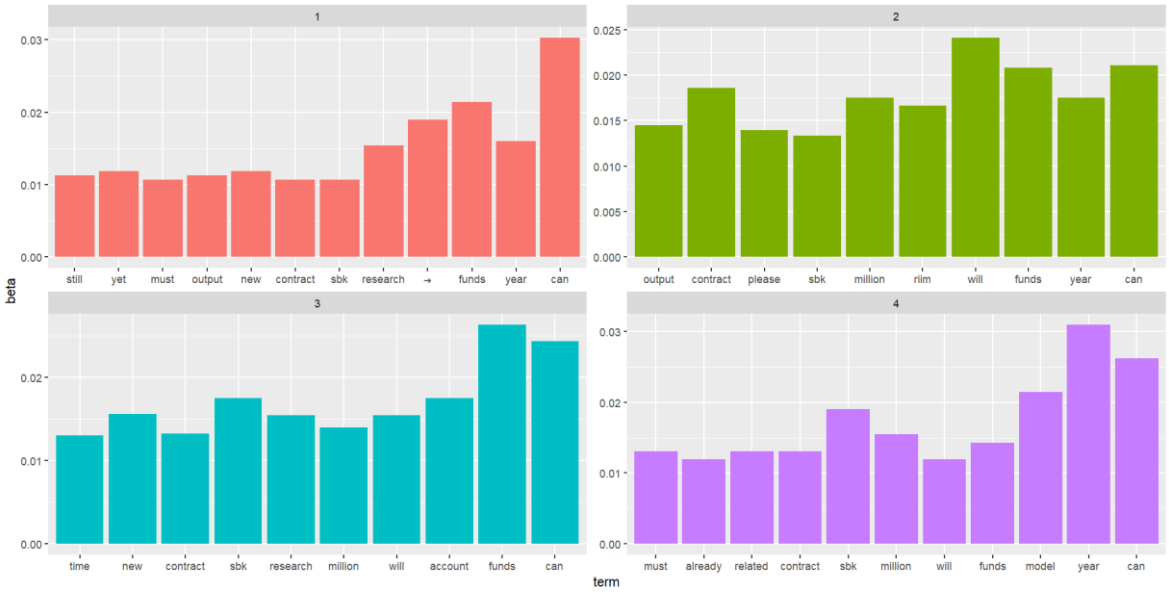

Figure 6. Topic Modelling Results

Topic 1 centers on administrative and implementation challenges, characterized by dominant terms such as still, yet, must, contract, sbk, research, and funds. These terms indicate ongoing procedural bottlenecks and unresolved operational issues, particularly inconsistencies between the directives of the Directorate of Research Funding and those of the Research Organizations. This topic highlights recurring concerns regarding contract management, fund utilization, and uncertainties in the timing of disbursement. Topic 2 focuses on funding rules and output requirements, with key terms such as output, contract, SBK, million, RIIM, and funds pointing to discussions about standardized funding ceilings (e.g., the commonly referenced 150 million rupiah) and the implications of SBK regulations on research deliverables. This topic reflects debates on how SBK-defined output categories shape performance indicators and contractual obligations among BRIN, LPDP, and researchers. Topic 3 captures issues related to system transition and financial account management. Dominant terms like time, contract, sbk, account, funds, and research underscore participants' concerns about account closure deadlines, contract extensions, and the administrative readiness needed to support smooth disbursement during the transition period. Finally, Topic 4 addresses output alignment and performance evaluation. Terms such as model, year, contract, sbk, and million point to discussions about the requirement for tangible outputs, such as models or prototypes, particularly for projects receiving higher funding allocations. This topic reflects apprehensions among researchers in the social sciences and humanities, who often face structural challenges in meeting output expectations that are typically designed for more technology-oriented research. Together, these four topics provide a comprehensive view of the operational, procedural, and conceptual issues shaping stakeholder experiences during the adoption of the SBK-based research funding system.

4. DISCUSSIONS

The text-mining analyses, encompassing word cloud visualization, sentiment analysis, emotion analysis, and topic modeling, identify several recurring issues in the transition toward the SBK output-based funding mechanism. These include ambiguity in output classification, administrative inconsistencies, transitional uncertainty, and limited stakeholder engagement. While both supportive and concern-oriented expressions are observed in the corpus, the findings primarily reflect patterns derived from the distribution of lexical and thematic features within the FGD data.

To situate these findings within a systematic evaluative framework, this study applies Dunn's policy evaluation criteria, enabling a structured mapping of how the identified issues relate to effectiveness, efficiency, adequacy, equity, responsiveness, and appropriateness [6]. This framework provides an analytical basis for interpreting the empirical results and linking them to potential areas for policy refinement, as summarized in Table 2.

First, the analysis highlights the role of output classification as a recurring topic in the dataset, particularly in relation to differences across research disciplines. The findings suggest that ambiguity in distinguishing between physical outputs (such as models and prototypes) and non-physical outputs (such as publications or conceptual frameworks) is frequently discussed within the corpus. This indicates that further clarification and differentiation of output categories may be beneficial for improving alignment across disciplines.

Second, the results point to frequent references related to administrative procedures and coordination, indicating the prominence of issues surrounding financial accountability, contractual arrangements, and institutional roles. These patterns suggest that clearer guidance and more consistent implementation mechanisms may support improved administrative coherence.

Third, themes associated with timelines, accounts, and procedural changes indicate recurring discussions on transition-related challenges. These findings imply that the transition toward SBK-based mechanisms may require structured provisions to ensure continuity and minimize disruptions during implementation.

Finally, patterns observed in sentiment and emotion analysis indicate that stakeholders express both concern-related and forward-looking language. This suggests that discussions are characterized by a combination of critical reflections and expectations for improvement, highlighting the importance of maintaining effective communication and engagement mechanisms.

Taken together, the association between empirical findings and Dunn's policy evaluation criteria is based on the conceptual alignment between observed patterns in the data and the functional dimensions of policy performance. For example, issues related to ambiguity in output classification are linked to effectiveness and equity, as they affect both the achievement of policy objectives and fairness across research disciplines. Similarly, recurring administrative concerns are associated with appropriateness and effectiveness, reflecting the need for clearer implementation mechanisms. This mapping is therefore interpretive and intended to provide a structured lens for relating empirical patterns to policy evaluation dimensions.

Table 2. Mapping of Analytical Findings to Dunn's Evaluation Criteria

No.	Rationale Derived from 2025 Findings	Relevant Dunn Criteria	Implication for Policy Refinement
1	Frequent discussion of output classification ambiguity across disciplines	Effectiveness, Equity, Appropriateness, Adequacy	Need for clearer and more flexible differentiation of research output categories across disciplines
2	Recurring references to administrative processes and coordination issues	Effectiveness, Appropriateness	Improved clarity in administrative procedures and coordination between institutional units
3	Recurrent concerns related to timelines, accounts, and transition processes	Adequacy, Responsiveness, Effectiveness	Development of structured transition mechanisms to support continuity during policy shifts
4	Coexistence of trust-related and concern-related expressions in stakeholder discourse	Responsiveness, Equity, Appropriateness	Strengthening stakeholder engagement and communication mechanisms

5. CONCLUSION

This study demonstrates how text-mining techniques can be applied to extract policy-relevant insights from unstructured governance-related text, using FGD verbatim transcripts on Indonesia's transition to the SBK-based research funding mechanism as a case study. The analysis identifies recurring patterns in the data, particularly related to administrative coordination, output classification, and transitional uncertainty. These findings are derived from the combined use of topic modeling, sentiment analysis, and emotion analysis, which capture both thematic structure and affect-related language within the corpus.

From a methodological perspective, the study illustrates the potential of combining multiple text-mining approaches to support evidence-based policy analysis. At the same time, it highlights important methodological considerations, including the limitations of lexicon-based sentiment and emotion analysis in capturing contextual meaning, the sensitivity of results to preprocessing choices, and the constraints associated with relatively small and translated corpora.

In terms of policy implications, the results provide empirical insights that may inform the refinement of research funding policies. For example, topics related to output classification ambiguity and disciplinary differences suggest a need for clearer differentiation of research outputs. Similarly, the prominence of administrative and coordination-related terms indicates areas where procedural clarity may be improved. Patterns related to timelines and transition processes further point to the importance of structured implementation mechanisms, while the coexistence of trust-related and concern-related expressions highlights the role of stakeholder engagement in policy development. These implications are intended as evidence-informed considerations rather than prescriptive recommendations.

However, several limitations should be acknowledged. The use of English-based lexicons for Indonesian-language data may not fully capture culturally embedded meanings and linguistic nuances specific to the Indonesian context. In addition, probabilistic topic models such as LDA simplify complex policy narratives into discrete themes, which may not fully represent the contextual richness and interconnections among policy issues discussed by participants. Furthermore, the study

adopted an interpretability-driven approach in specifying the number of topics, without employing formal model-selection metrics such as topic coherence scores or perplexity. While this approach aligns with the exploratory objectives of the study and facilitates substantive interpretation of the results, future research may benefit from incorporating quantitative model evaluation measures to assess the robustness and stability of alternative topic structures.

Finally, beyond the specific case of RIIM, this study suggests that text-mining approaches can be applied more broadly to other governance settings where policy-relevant information is embedded in unstructured textual data. By systematically analyzing stakeholder discourse, such approaches can complement traditional evaluation methods and support more empirically grounded policy design and implementation.

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