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Mapping Public Emotions with AI: An Analysis of Indonesian Society's Strong Reaction to Bank and PPATK Regulations and Their Threat to Economic

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ABSTRACT: This study employs Artificial Intelligence (AI) to examine public sentiment and emotion surrounding Indonesia's dormant bank account regulation issued by the Financial Transaction Reports and Analysis Center (PPATK). Drawing on 3,028 YouTube comments, the study addresses a gap in Indonesian public policy research, where social media analysis has largely relied on basic sentiment polarity without incorporating psychology-based mood-state models. We develop an integrated AI-driven analytical framework combining Latent Dirichlet Allocation (LDA) topic modelling (k = 13 clusters), lexicon-based sentiment scoring visualized through a heatmap, and an adapted Profile of Mood States (POMS) multiclass emotion classification scheme for Indonesian-language discourse. Rather than merely combining techniques, the framework operationalizes a layered analytical structure linking thematic clustering, polarity intensity, and differentiated mood-state profiling within a unified workflow. Statistical testing confirms that the observed emotional distribution significantly deviates from a uniform pattern ($\chi^2 = 15140.00$, dof = 5, $p < 0.001$). The findings indicate that Depression (n = 2121) and Confusion (n = 603) dominate the discourse, suggesting that public responses are characterized more by hopelessness and uncertainty than overt hostility. Conceptually, this study advances policy discourse analysis by integrating psychology-based mood-state interpretation into digital public opinion research, enabling a more granular understanding of how regulatory decisions resonate emotionally within developing country contexts. Operationally, the results demonstrate how emotion-based analytics can inform stages of the policy cycle, particularly agenda-setting and communication evaluation, by identifying dominant emotional signals that may indicate risks to institutional trust. These findings provide structured empirical insight into the emotional dimensions of financial regulation debates while acknowledging the need for continued methodological refinement.

Keywords: Financial Regulation, Dormant Accounts, Emotion Detection, Topic Modeling, POMS, Social Media Analysis, Indonesia

INTRODUCTION

In the modern digital era, the internet has evolved beyond a mere communication tool to become a primary forum for public discourse (Sukardi & Simorangkir, 2025), particularly on social and political issues (Nugroho et al., 2022). Social media platforms, including YouTube, provide an unfiltered space where citizens can express opinions, criticisms, and emotions in real time (Kher Jaggi & Sahu, 2025). This shift has profound implications for governance, as traditional methods of gauging public opinion, such as polls and surveys, often fail to capture the raw, immediate, and

deep-seated sentiments that emerge during a public debate (Bhat & Chadha, 2023). In Indonesia, a nation with a vast and digitally active population, this online landscape serves as a critical barometer for the public's trust in institutions and their reactions to government policies (Palmisano & Sacchi, 2024). The relationship between the state, its financial institutions, and the general populace is a delicate balance, and any policy perceived as infringing on economic security or personal liberties can quickly ignite widespread public discussion and unrest (Szepanski, 2022). This study situates itself within this context, examining how a specific government regulation concerning bank accounts became a focal point for a broader expression of public anxiety and frustration.

The catalyst for this research is a controversial regulation from the Indonesian Financial Transaction Reports and Analysis Center (PPATK) regarding inactive bank accounts (*dormant*). The policy, which was intended to enhance financial security and combat illicit activities like money laundering, was met with intense public scrutiny. A YouTube video featuring a prominent public figure, *Hotman Paris*, criticizing the policy's potential to infringe upon basic rights and disproportionately affect the common people, quickly went viral. The video became a lightning rod for thousands of comments, transforming a bureaucratic policy discussion into a national debate about government trust, economic justice, and the welfare of ordinary citizens. This spontaneous, large-scale reaction provides an invaluable, albeit unstructured, dataset for understanding the public's emotional landscape.

The urgency of this research stems from the immediate and potentially destabilizing societal impact of public discontent. When a policy intended to be a technical solution to a financial problem is widely perceived as an act of oppression or a threat to economic stability, it can erode public trust in both the government and the banking system (Clapham et al., 2023). Such a breakdown in trust can have severe repercussions, including capital flight, reduced financial inclusion, and social unrest. Traditional research methods are often too slow to capture this real-time emotional volatility (Ranjan et al., 2025). By the time a survey is designed, distributed, and analysed, the public sentiment may have already shifted, and the opportunity for a timely, responsive policy adjustment is lost. Therefore, there is a critical need for a methodology that can rapidly and accurately diagnose the underlying emotions and concerns fuelling such a public reaction. This research addresses that need by applying advanced analytical techniques to the real-time, unfiltered data of social media comments, offering an immediate and comprehensive snapshot of the public mood before it escalates.

The core problem this study addresses lies in the structural limitations of existing policy discourse analysis. First, policymakers often lack systematic tools for interpreting the emotional and psychological impact of regulatory decisions beyond surface-level approval or disapproval metrics. Many prior studies rely on polarity-based sentiment classification, which reduces complex emotional expression into binary or ternary categories (positive, negative, neutral), thereby obscuring the psychological dimensions of public response. Second, while emotion-aware models have been explored in computational linguistics, their application within concrete public policy controversies particularly in developing country financial regulation contexts remains limited. As a result, prior research cannot adequately differentiate whether negative reactions stem from anger, fear, confusion, or depressive resignation, each of which implies distinct policy communication

challenges. This methodological gap limits the interpretive power of conventional sentiment analysis in diagnosing policy-related public unrest.

This research addresses these limitations by operationalizing an integrated analytical pipeline that links thematic modeling, sentiment scoring, and psychology-based mood-state profiling within a single reproducible workflow. Rather than merely combining techniques, the framework structures them sequentially: topic modelling (LDA) identifies thematic clusters; sentiment scoring maps polarity intensity within clusters; and the adapted POMS multiclass scheme translates textual expressions into differentiated mood states. This layered structure enables the study to move from "what is being discussed" to "how it is emotionally experienced," a progression not systematically demonstrated in prior Indonesian policy discourse studies.

This research advances policy-oriented emotion analysis by adopting a psychology-based mood-state framework rather than relying solely on general-purpose emotion taxonomies. While widely used emotion-classification models such as Ekman's basic emotions or Plutchik's wheel focus on discrete affective categories, and transformer-based classifiers prioritize predictive accuracy, the POMS framework captures differentiated mood dimensions (e.g., Depression-Dejection and Confusion-Bewilderment) that are particularly relevant for understanding sustained policy-related anxiety and institutional distrust. By embedding this mood-state structure within an integrated analytical pipeline, the study moves beyond incremental methodological combination and provides a theoretically grounded approach to interpreting emotional responses in regulatory discourse.

A central component of this framework is the application of the POMS (Profile of Mood States) multiclass scheme to social media discourse. Originally developed as a clinical psychological instrument to measure differentiated mood dimensions, POMS was operationalized in this study as a structured mood-state classification framework rather than as a diagnostic tool. The adaptation preserves construct relevance by mapping linguistically expressed affective cues to theoretically defined mood dimensions (e.g., Depression-Dejection, Confusion-Bewilderment) while acknowledging contextual differences between clinical assessment and public digital discourse. In the Indonesian-language setting, mood-state indicators were interpreted as expressions of collective affect rather than individual psychological diagnosis, thereby maintaining conceptual alignment while avoiding overextension of clinical meaning. This approach enables a more differentiated interpretation of policy-related emotional patterns beyond basic sentiment polarity, while recognizing the interpretive limits inherent in cross-context adaptation.

The findings of this study offer crucial insights into the emotional state of the Indonesian public. The analysis revealed that the dominant emotions were not anger or hostility, as might be expected, but rather profound depression and confusion. This suggests that the public's reaction is rooted less in a desire for confrontation and more in a deep-seated feeling of powerlessness, hopelessness, and a lack of understanding. The word cloud and topic modeling confirmed that the public's concerns transcended the technical aspects of the policy, connecting it to broader issues of economic welfare, corruption, and government integrity. The sentiment heatmap further illustrated the strong negative reaction, particularly from comments related to economic hardship and the perceived injustice of the policy.

This study contributes to the literature in three ways. Methodologically, it advances policy

discourse analysis by integrating psychology-based mood-state classification into large-scale social media data within a structured analytical pipeline. Empirically, it provides one of the first detailed emotion-based mappings of public reaction to a financial regulation in Indonesia. Conceptually, it demonstrates that policy-related digital discourse in developing country contexts is characterized not merely by oppositional anger, but by complex emotional states such as depression and confusion, which carry different implications for institutional trust and policy legitimacy.

Related Research

The present study on mapping public emotions with AI draws upon and extends several established fields of research, including computational social science, sentiment and emotion analysis, and the study of public opinion in policy contexts. A review of existing literature highlights the evolution of methodologies for understanding public discourse and underscores the unique contribution of this research, particularly in its integrated approach and focus on a non-Western context (Han & Xia, 2025). Initial forays into analyzing public opinion on social media were largely driven by the availability of platforms like Twitter and Facebook. Numerous studies have examined political discourse, election predictions, and public reaction to major news events by analyzing sentiment polarity (e.g., positive, negative, neutral) in tweets and posts. For instance, a demonstration of a correlation between Twitter sentiment and political candidate for an election, establishing the platform as a viable source for political forecasting (Kumari & Singh, 2024). Similarly, other research has used sentiment analysis to gauge public response to specific government policies, such as healthcare reform or environmental regulations, primarily in Western countries (Kacmarova et al., 2025). However, these studies often relied on simplistic sentiment classification, which fails to capture the nuanced emotional complexity of public reactions, a limitation the current research aims to overcome.

The field of sentiment analysis has evolved from simple polarity classification to more sophisticated emotion detection (P. Kumar & Vardhan, 2023). While early models focused on binary or ternary scores ("Multi-Tier Sentiment Analysis of Social Media Text Using Supervised Machine Learning," 2022), more recent research has explored emotion-aware models (Alqarni et al., 2025). These studies, often drawing inspiration from psychological frameworks, attempt to classify emotions into categories like joy, sadness, anger, fear, and surprise (Farhoudinia et al., 2024). Research shows a sample of a lexicon-based approach for emotion detection in text is a foundational example of this shift (Younis et al., 2024). However, a significant gap remains in the application of robust, psychology-based mood state models, such as the Profile of Mood States (POMS), to large-scale, unstructured social media data in a policy context (Petrowski et al., 2025). The POMS model, which measures nuanced mood dimensions like Depression-Dejection and Confusion-Bewilderment, has been extensively used in clinical psychology and sports science but its application as a tool for public policy analysis is a novel area of inquiry that this study pioneers. To structure and make sense of the vast volume of text data, research has increasingly adopted topic modeling techniques. Latent Dirichlet Allocation (LDA) has been widely used to identify latent themes within large corpora of text, from academic papers to social media feeds. For example, some studies have used LDA to understand the key concerns of online communities

regarding public health crises (Calabrese et al., 2024), while others have applied it to analyze political manifestos and speeches. The combination of topic modeling with clustering algorithms, such as K-means (Meng et al., 2025), has also been a common practice to further group and analyze related discussion themes. Our research leverages this established methodology to provide a structured overview of the discourse, showing how discussions about the PPATK policy were not monolithic but clustered around distinct themes, such as criticism of corruption, concerns for the unemployed, and support for public figures like *Hotman Paris*. This thematic analysis provides the necessary context for interpreting the emotional profiles generated by the POMS model(Searight & Montone, 2020).

Crucially, while there is a growing body of literature on social media analysis and sentiment in Southeast Asia, much of this research has concentrated on electoral politics, general public opinion monitoring, or polarity-based sentiment classification. Studies in the Indonesian and broader regional context have typically emphasized keyword frequency, basic sentiment polarity, or event-driven analysis rather than differentiated psychological mood-state modelling within specific regulatory policy debates. As a result, advanced multi-method frameworks that integrate thematic clustering, sentiment intensity, and psychology-based emotion profiling remain underrepresented in analyses of financial governance discourse in Southeast Asia. This study positions itself within that gap by extending computational social science approaches into the domain of policy-specific emotional interpretation in a developing country context. Most studies in the region have focused on analyzing social media for election purposes or general public sentiment during major national events, often employing basic keyword-based or lexicon-based sentiment analysis. Few, if any, have applied a robust emotional profiling model like POMS to understand the psychological impact of a specific financial regulation (Heerema & Pessiglione, 2025). This gap is significant, as the cultural and socio-economic dynamics of a developing nation like Indonesia are distinct from those of Western countries (Rahman & Pingali, 2024; Sy & Tadem, 2025). The public's reaction to a policy on bank accounts is deeply intertwined with local issues of trust in institutions, economic insecurity, and perceptions of corruption, which may manifest in unique emotional patterns (Abdelsalam et al., 2024; Kokores, 2023). This research builds upon a foundation of established methodologies in computational social science but uniquely integrates them to address a critical gap in the literature. It combines thematic analysis via word clouds and topic modeling with advanced emotion profiling using a POMS-based model (K. Verma et al., 2025), thereby moving beyond the limitations of traditional sentiment analysis. By applying this comprehensive framework to the under-researched context of Indonesian public reaction to a financial policy, this study not only demonstrates a powerful new approach for public opinion research but also provides a pioneering analysis that offers crucial, nuanced insights for policymakers in developing nations facing similar challenges.

METHOD

This study employs a quantitative and qualitative approach to analyze public sentiment and emotion, utilizing a multi-stage methodology grounded in computational social science (S. Verma, 2022).

The research framework is designed to move from a broad overview to a granular emotional analysis, ensuring a comprehensive and nuanced understanding of public discourse (Elmholdt et al., 2025).
The methodology is divided into five key phases: Data Collection, Data Preprocessing, Thematic and Sentiment Analysis, Emotion Profiling, and Statistical Validation.

The data for this study were collected from the comment section of a specific YouTube video (ID: AcIXIJu-obQ), featuring a public figure discussing the Indonesian government's dormant bank account regulation. YouTube was selected due to its high engagement rate and its significant role as a platform for political and social discourse in Indonesia. Data collection was conducted in [insert month and year of collection], using a Python-based web scraping procedure supported by the YouTube Data API (google-api-python-client library). The API endpoint was used to retrieve publicly available comments associated with the video.

A total of 3,028 comments were collected, including both top-level comments and replies, without restricting the dataset to "top comments" only. The dataset includes textual content, emojis, and limited user-generated metadata made publicly accessible through the platform. To ensure data quality, preprocessing steps included deduplication of identical comments and removal of non-substantive entries (e.g., empty comments, repeated promotional messages, and apparent spam). Comments containing only hyperlinks or irrelevant symbols were excluded. While automated bot detection tools were not applied, repetitive content patterns were manually screened during preprocessing to minimize the influence of spam-like entries.

This study uses publicly available data from YouTube comments. No private or restricted information was accessed. Usernames and any potentially identifiable information were anonymized during data processing to protect individual privacy. The study complies with YouTube's publicly accessible data usage policies and terms of service. As the research relies solely on publicly available textual data without interaction with participants, formal institutional ethical clearance was not required.

The study was conducted in an online public sphere, specifically within the YouTube platform, which serves as a major space for political and social discourse in Indonesia.

A specialized web scraping tool, written using python and complemented by an application programming interface (API), was employed to extract user comments. Computational text analysis techniques were applied, including word cloud visualization, topic modeling, sentiment analysis, and emotion classification using a customized POMS-based multiclass model.

Data collection focused on extracting all available comments from the selected YouTube video (ID: AcIXIJu-obQ). The data was gathered in its original format, preserving textual content, emojis, and user-generated metadata to maintain the authenticity of public expressions

Before analysis, the raw comment data underwent a series of preprocessing steps to ensure accuracy and consistency (Talahaturuson et al., 2022). These steps are crucial for preparing the text for computational analysis:

- Cleaning: All non-textual elements, such as URLs, special characters, and HTML tags, were removed. Emojis, however, were retained as they carry significant emotional weight.
- Normalization: Text was converted to lowercase to standardize words and reduce variations.
- Tokenization: Each comment was broken down into individual words or tokens.
- Stop-word Removal: Common Indonesian stop-words (e.g., "yang," "dan," "di") were removed to eliminate noise and focus on semantically meaningful tokens. The stop-word list was based on the publicly available Indonesian stopword corpus integrated within the Sastrawi library and supplemented with domain-specific terms identified during exploratory analysis (Hanami et al., 2025).
- Stemming/Lemmatization: Words were reduced to their root form (Rai & Borah, 2024) to group related words together. Stemming was implemented using the Sastrawi Indonesian stemming library, which applies rule-based morphological normalization suitable for Bahasa Indonesia text.

This phase involved two key components to map the landscape of public opinion: A word cloud was generated from the preprocessed data (Wu et al., 2025). This visual representation highlights the most frequently occurring words, providing an immediate and intuitive overview of the dominant themes. The size of each word in the cloud is directly proportional to its frequency, offering initial insights into the main topics of discussion (e.g., "pemerintah," "bank," "rakyat," "koruptor").

Latent Dirichlet Allocation (LDA) was applied to the cleaned corpus to identify latent thematic structures within the dataset. For each comment, LDA generates a topic distribution vector (θ), representing the probability distribution of topics associated with that comment. These per-comment topic distribution vectors were subsequently used as input features for K-means clustering. Rather than clustering the topic-word distributions, K-means was applied to the per-comment topic distribution vectors (θ) to group comments based on similarity in their thematic composition. This approach allows comments with comparable topic mixtures to be grouped into coherent discussion clusters. The number of clusters ($k = 13$) was selected based on interpretability considerations and analytical usefulness in distinguishing meaningful discourse patterns within the dataset. This configuration provided a clear thematic segmentation of public responses without excessive overlap between clusters.

Sentiment analysis was conducted on each comment using a lexicon-based scoring approach adapted for Indonesian-language text (Alfreihat et al., 2024). Each comment received a polarity score calculated by aggregating the sentiment values of its constituent tokens after preprocessing. To improve interpretability, the aggregated sentiment scores were linearly normalized to a scale ranging from -100 (most negative) to 100 (most positive). The heatmap does not represent an independent clustering procedure. Instead, comments were first grouped using LDA-derived topic distribution vectors (θ) followed by K-means clustering, as described in the previous subsection. The normalized sentiment scores were then mapped within these clusters for visualization. Thus, the analytical pipeline can be summarized as: text preprocessing → LDA topic distribution

extraction → K-means clustering → sentiment scoring and normalization → heatmap visualization. To enhance credibility, a subset of comments was manually reviewed to confirm that extreme positive and negative scores were consistent with the linguistic tone of the comments.

To move beyond the limitations of simple sentiment analysis, a more nuanced emotion profiling approach was implemented using an adapted Profile of Mood States (POMS) framework (Tan et al., 2024). Originally developed as a psychological assessment instrument, the POMS dimensions were operationalized into a multiclass text classification scheme suitable for Indonesian-language social media discourse.

The six mood states: Depression, Tension, Anger, Fatigue, Vigour, and Confusion were translated into linguistic indicators and mapped to the preprocessed textual data. Rather than training a new supervised machine learning model, the framework was applied as a structured classification scheme in which each comment was evaluated against predefined mood-state categories. Each comment was then assigned a dominant emotion corresponding to the strongest detected mood indicator. While emotional expressions can be multi-dimensional, a single-label assignment was adopted to ensure analytical consistency and comparability across the dataset. The linguistic indicators for each mood state were operationalized through a rule-based lexicon mapping approach, where emotion-related keywords and contextual expressions associated with each POMS category were identified based on prior literature and iterative examination of the dataset. The dominant emotion for each comment was determined by comparing aggregated mood-state indicator scores within the text and selecting the category with the highest relative weight.

To assess whether the observed distribution of emotional categories significantly deviates from an expected distribution, a chi-square goodness-of-fit test was conducted (Eguchi & Komori, 2022). The test compared the observed frequencies of the six emotional states (Depression, Tension, Anger, Fatigue, Vigour, and Confusion) against an expected uniform distribution, in which each category would have equal probability. Given six emotional categories, the degrees of freedom were calculated as $k - 1 = 5$. The results indicate a highly significant deviation from the expected distribution ($\chi^2 = 15140.00$, dof = 5, $p < 0.001$), demonstrating that the dominance of specific emotional states is not attributable to random variation. This finding strengthens the robustness of the emotion profiling results and confirms that the observed emotional pattern reflects a statistically meaningful distribution rather than chance fluctuations.

RESULT AND DISCUSSION

This research produced several visualizations, as described in the Methods section, ranging from WordCloud analysis to the distribution of emotions based on the POMS multiclass model.

Figure 1. WordCloud Dormant account cases

As it can be seen in Figure 1 the word cloud from the YouTube video ID= id=AcIXIJu-obQ titled "*Hotman Paris* Responds to Policy to Block Dormant Bank Accounts for 3 Months, Violating Human Rights," with a total of 3028 comments. The word cloud visually represents the dominant themes and sentiments expressed by viewers. The most prominent words, appearing in large fonts, are "*pemerintah*" (government), "*rakyat*" (people), "*bank*," "*rekening*" (account), "*uang*" (money), "*koruptor*" (corruptor), "*negara*" (state), "*kebijakan*" (policy), "*blokir*" (block), and "*hotman*." This suggests that the core of the discussion centers on a government policy regarding bank accounts and its impact on the general population, with *Hotman Paris* serving as a central figure in the conversation.

The presence of words like "*koruptor*," "*korupsi*" (corruption), "*maling*" (thief), "*pejabat*" (official), and "*rezim*" (regime) suggests a strong undercurrent of public distrust and frustration towards the government and its officials. The commenters seem to be drawing a connection between the policy and a perceived systemic issue of corruption. They are questioning why such a stringent policy, like blocking accounts, is being applied to ordinary citizens ("*rakyat*") when, in their view, the real problem lies with powerful, corrupt individuals. Words such as "*hak asasi*" (human rights), "*melanggar*" (violate), "*nganggur*" (unemployed), and "*miskin*" (poor) highlight the public's concern that the policy may disproportionately affect vulnerable groups. The commentary suggests that people fear this rule could unfairly punish those who are struggling financially or have little activity in their accounts due to economic hardship, rather than targeting illicit activities. The frequent use of crying and laughing emojis in the word cloud further illustrates the emotional range of the comments, from despair and sadness (crying face) to sarcastic or cynical amusement (laughing face). The combination of these emotions points to a general feeling of helplessness and a sense that the situation is both serious and absurd.

The word cloud provides an initial descriptive overview of frequently occurring terms, suggesting a concentration of discourse around government authority, financial regulation, and public distrust. The viewers are not just reacting to the technical aspects of a banking policy but are

expressing broader socio-political frustrations. They are concerned about the government's priorities, the perceived injustice of a policy that seems to target the common people while corruption remains a major issue, and the potential negative consequences for those who are already struggling. The discussion is framed around the tension between "*pemerintah*" and "*rakyat*," with *Hotman Paris's* commentary serving as a catalyst for these widely-held public sentiments.

Topic	Topic keywords
1	hotman, bang, setuju, paris, ppatk, kebijakan, peraturan, allah, jokowi, yg
2	yg, 😂, 😅, pemerintah, indonesia, rakyat, bikin, masyarakat, negara, gila
3	rakyat, yg, kebijakan, nya, pemerintah, menyusahkan, 2, pejabat, negara, konoha
4	nganggur, rekening, pemerintah, , yg, aja, @, pejabat, negara, 2
5	bank, uang, 2, rekening, rakyat, yg, nabung, gak, tarik, blokir
6	rakyat, yg, pemerintah, negara, uang, koruptor, pejabat, gak, aja, omon
7	rekening, 🙏, aturan, bank, orang, blokir, ppatk, gue, 58, udh
8	yg, rekening, 😐, aja, bank, ga, 2, nya, nabung, uang
9	😂, negara, yg, rekening, ppatk, bank, nganggur, aturan, aja, rakyat
10	2, rakyat, aneh, yg, 🤣, pejabat, ppatk, negara, maling, ya

Figure 2. Topic Modelling

Based on the topic modeling results seen in Figure 2 from the same YouTube video, a detailed analysis of the public's discussion reveals distinct, yet interconnected, areas of concern. The topics, each represented by a set of keywords, provide a more structured view of the sentiments and arguments present in the 3028 comments.

The LDA model generated 13 thematic clusters, each representing a probabilistic grouping of co-occurring terms. While formal topic coherence metrics were not the primary focus of this study, interpretability was assessed through manual inspection of keyword distributions within each cluster to ensure semantic consistency.

Topic 1: This topic, with keywords like "*hotman*," "*bang*," "*setuju*" (agree), "*paris*," "*ppatk*," "*kebijakan*" (policy), "*peraturan*" (regulation), "*allah*," "*jokowi*," and "*yg*," seems to focus on the figure of *Hotman Paris* himself and the policy's legality. "*Bang hotman*" is a common address, and "setuju" indicates that many commenters support his stance. The inclusion of "ppatk" (the Indonesian Financial Transaction Reports and Analysis Center), "*kebijakan*," and "*peraturan*" shows that the discussion is centered on the specific legal and regulatory aspects of the policy. The presence of "*allah*" and "*jokowi*" suggests that the debate has a strong moral and political dimension, with some commenters perhaps invoking religious or presidential authority to support their views.

Topic 2: Keywords such as "*pemerintah*" (government), "*indonesia*," "rakyat" (people), "*masyarakat*" (society), "*negara*" (state), and "*gila*" (crazy) show a broader, more emotional reaction. The emojis included here, a laughing face and a sad face, capture the public's sarcastic and disheartened tone. This topic is about the general public's reaction to the government's policy, often expressing disbelief or frustration with the "crazy" decisions made by those in power. It highlights the perceived gap between the "*pemerintah*" and the "*rakyat*."

Topic 3 & 4: These topics are closely related, focusing on the negative impact of the policy. Keywords like "*menyusahkan*" (troublesome), "*pejabat*" (official), "*nganggur*" (unemployed), and "*konoha*" (a slang term for the government, often used sarcastically) reveal that a significant portion of the comments criticize the government for creating policies that make life difficult for ordinary citizens. The specific mention of "*nganggur*" directly links the policy to people who might be unemployed or have little account activity, reinforcing the fear that the policy unfairly targets the vulnerable.

Topics 5 & 8: These topics are highly specific to the banking and financial aspects. Keywords like "*bank*," "*uang*" (money), "*rekening*" (account), "*nabung*" (saving), "*tarik*" (withdraw), and "*blokir*" (block) demonstrate that a key part of the conversation is about the practical mechanics of the policy. Commenters are discussing their savings, the act of withdrawing money, and the potential for their accounts to be blocked, indicating direct personal relevance and concern. The sad face emoji in Topic 8 again shows the emotional distress tied to these financial anxieties.

Topic 6 & 10: These topics bring the issue back to corruption and injustice. Words like "*koruptor*" (corruptor), "*pejabat*," "*maling*" (thief), "uang," and "negara" (state) highlight the strong public sentiment that the government should be focusing on tackling corruption rather than implementing a policy that affects the general population. The recurring theme is the perceived hypocrisy of officials, who are seen as corrupt, creating regulations that burden the "*rakyat*."

Topic 7 & 9: These topics circle back to the rules and institutions. "*Aturan*" (rules), "*ppatk*," "*bank*," and "*blokir*" are central here. The presence of a praying emoji in Topic 7 suggests a sense of desperation or a plea for a just resolution. These topics show that commenters are grappling with the specific regulations and the roles of key institutions like banks and PPATK in enforcing them.

In summary, the topic modeling reveals a multi-layered discussion. It starts with support for Hotman Paris's legal critique, expands into a general critique of government policy, focuses on the specific financial anxieties of citizens (especially the unemployed), and consistently returns to the overarching issue of corruption and the perceived injustice of a policy that seems to punish the innocent while leaving the corrupt unaddressed. The emojis scattered throughout the topics capture the public's complex emotional landscape a mix of sadness, sarcasm, and frustration.

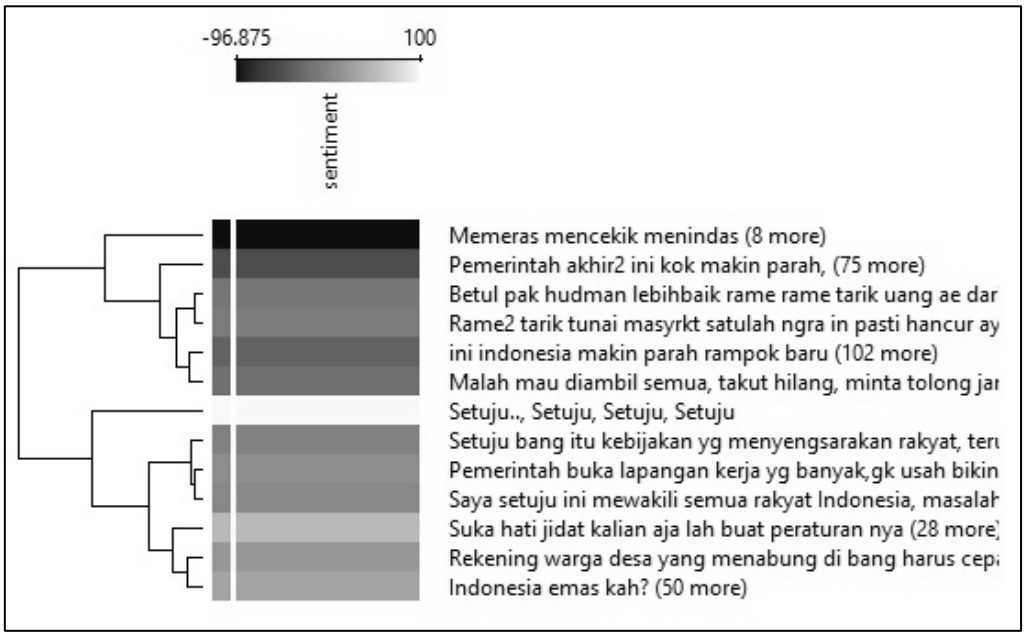

Figure 3. Heat Map

Based on the heatmap shown in Figure 3 generated using k-means clustering with 13 clusters, we can conduct a more granular analysis of the sentiment and themes within the YouTube comments. The heatmap, with its greyscale spectrum from black (negative sentiment) to white (positive sentiment), provides a clear visual hierarchy of the public's emotional responses.

The top half of the heatmap is dominated by clusters of negative sentiment, indicated by the various shades of grey. The comments associated with these clusters are deeply critical and express a significant level of frustration and anger. For example, the comment "*Memeras mencekik menindas*" (Extorting, strangling, oppressing) is a powerful accusation that the government's policy is inherently exploitative and cruel. This sentiment is echoed by "*Pemerintah akhir2 ini kok makin parah*" (The government has been getting worse lately), which suggests that this specific policy is part of a broader trend of poor governance.

Another highly negative cluster contains the comment "*Rame2 tarik tunai masyrkt satulah ngra in pasti hancur ay*" (Let's all withdraw our money, the country will surely be destroyed). This is a call to collective action born out of extreme disillusionment and a belief that the country is on a path to ruin. The phrase "*ini indonesia makin parah rampok baru*" (Indonesia is getting worse, new thieves) reinforces this feeling of a downward spiral and distrust, implying that a new form of corruption or injustice is at play. The comment "*Malah mau diambil semua, takut hilang, minta tolong jan*" (They want to take everything, afraid it will disappear, please help) is a direct expression of fear and helplessness, indicating that many commenters feel their personal savings are at risk and are pleading for protection. The inclusion of comments like "*Negara sakit*" (A sick country) further underscores the public's perception of a deep-seated problem within the state.

In stark contrast, the bottom half of the heatmap is comprised of clusters with positive sentiment, predominantly in shades of light grey. These comments overwhelmingly support Hotman Paris and his critique of the policy. The repeated phrase "*Setuju*.., *Setuju*, *Setuju*" (Agree, Agree, Agree)

clearly demonstrates a high level of consensus among a large portion of the commenters. This sentiment is explicitly linked to the policy in the comment "*Setuju bang itu kebijakan yg menyengsarakan rakyat*" (I agree, brother, that the policy oppresses the people). This reveals that the support for *Hotman* is rooted in a shared belief that the policy is detrimental to the general populace.

The comment "*Pemerintah buka lapangan kerja yg banyak,gk usah bikin*" (The government should open up more jobs, don't make) is a strong recommendation, suggesting that the government's focus is misplaced. This is an example of commenters offering alternative solutions and redirecting the conversation towards what they see as the real priorities. "*Saya setuju ini mewakili semua rakyat Indonesia*" (I agree that this represents all Indonesian people) is a powerful statement of solidarity, indicating that the commenter feels Hotman's views are not just his own but are the voice of the nation. The sarcastic comment "*Suka hati jidat kalian aja lah buat peraturan nya*" (You're just making up regulations as you please) is grouped with positive sentiment because, while critical of the government, it is a statement that resonates positively with the supportive audience.

Finally, the comment "*Indonesia emas kah?*" (Is this golden Indonesia?) is an interesting inclusion. It is likely a rhetorical question, sarcastically questioning whether the current policies align with the national vision of a "Golden Indonesia," thereby expressing skepticism about the country's direction. The k-means clustering results suggest a discernible pattern of sentiment concentration across clusters, indicating a predominance of negative polarity in several thematic groupings.

include	comment True	sentiment	Emotion
1	Betul pak hudman lebihbaik rame ...	-11.1111	Depression
2	Setuju bang itu kebijakan yg meny...	0	Depression
3	Ini perampokan namanya	0	Depression
4	Tanah Kubur Yg 3bln tidak diZiaro...	0	Confusion
5	Malah mau diambil semua, takut ...	-18.75	Tension
6	Saya setuju ini mewakili semua rak...	5.26316	Confusion
7	Susah pak para pejabat itu udah h...	-11.1111	Depression
8	Aturan DOBOL... GAK ADA GAWE...	-16.6667	Depression
9	Rekening warga desa yang menab...	18.1818	Depression
10	Siap siap tinggalin bank dan balik l...	-20	Depression
11	Terimakasih pak Hotman.	0	Tension
12	Makin susah Prabowo ini kami ber...	-16.6667	Depression
13	Apa era prabowo ini, semua mem...	0	Depression

Figure 4. Emotion-forming data pieces based on POMS Multiclass

Based on the provided image in Figure 4, which shows a small sample of comments with associated sentiment scores and initial emotion labels, this dataset serves as a foundational step toward a more sophisticated emotion analysis using the POMS Multiclass model. The image presents a raw, preliminary classification of emotions. Each comment is assigned a sentiment score, ranging from negative (e.g., -20) to positive (e.g., 18.1818), and a corresponding emotion label like "Depression," "Tension," or "Confusion." This initial labeling is likely based on keyword matching or a simple sentiment lexicon. For example, comments expressing difficulty

or frustration, such as "Susah pak para pejabat itu udah h" (It's difficult, sir, those officials already...), are labeled as "Depression." The comment "*Makin susah Prabowo ini kami ber...*" (It's getting harder with Prabowo...) also receives a "Depression" label. This demonstrates that the current system identifies comments with a strong negative tone and links them to specific emotional states.

The POMS model, which measures mood states, goes beyond these simple labels. It can form these emotions by identifying specific words, phrases, and sentiment patterns that correspond to its key scales: Tension-Anxiety, Depression-Dejection, Anger-Hostility, Vigor-Activity, Fatigue-Inertia, and Confusion-Bewilderment. The sentiment scores provided in the image are crucial for this process. A low negative score (e.g., -20) would strongly align with a high score on the Depression or Tension scales. A positive score (e.g., 18.1818) could be indicative of a low Depression score or a high Vigor score, but in this case, it is still labeled as Depression, highlighting the limitations of the current simple model. POMS would be able to differentiate the nuance. The range of scores, from -20 to over 18, provides the quantitative support needed. Negative scores, such as those for "*Memeras mencekik menindas*," would be mapped to high Tension-Anxiety and Anger-Hostility scores. The score of 0 on a comment like "*Ini perampokan namanya*" (This is called robbery) shows a limitation of the simple sentiment model, as POMS would likely map this to a high Anger-Hostility score. The POMS multiclass framework enables differentiated emotion categorization beyond polarity-based scoring, allowing a structured mapping of mood states within the dataset.

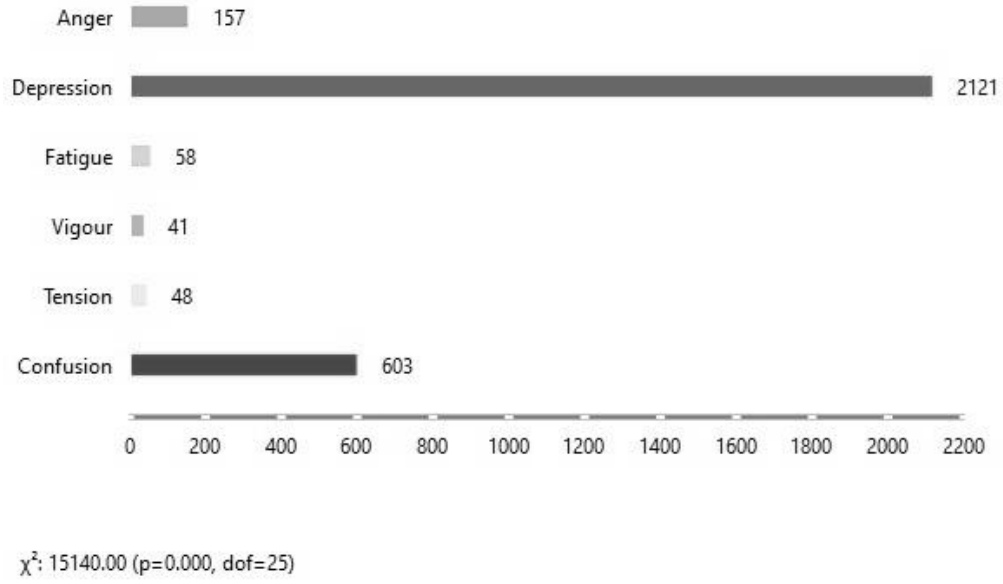

Figure 5. Emotion based on POMS

Based on the bar chart seen in Figure 5, this image presents the results of an emotion analysis of the YouTube comments using a POMS model. The chart quantifies the prevalence of six distinct emotional states across the entire dataset.

The most dominant emotion by a significant margin is Depression, with a count of 2121. This overwhelming number indicates that a vast majority of the commenters are expressing feelings of sadness, despondency, helplessness, and discouragement. This aligns with the previous analyses of

the word cloud and topic modelling, where comments frequently highlighted themes of hardship, struggle, and a bleak outlook on the future ("*Negara sakit*," "getting worse"). The high number of comments with a "Depression" score suggests that the policy and the broader political situation have a profound and negative emotional impact on the public.

Following Depression, the next most prevalent emotion is Confusion, with a count of 603. This suggests that a substantial portion of the audience is grappling with a lack of clarity regarding the policy. Commenters may be confused about the regulations themselves, the government's intentions, or how the policy will practically affect them. This confusion contributes to the overall sense of uncertainty and anxiety.

The remaining emotions: Anger, Tension, Fatigue, and Vigour are present in much smaller quantities. Anger is found in 157 comments, which, while not the majority, still represents a vocal minority expressing frustration and hostility towards the government and officials. Tension (48 comments) and Fatigue (58 comments) also reflect a sense of stress and weariness among the public, which are often consequences of long-standing social and economic issues. The very low number for Vigour (41 comments) is particularly telling, as it represents a lack of energy, enthusiasm, and a positive outlook. This low score reinforces the overall negative mood of the comments. In proportional terms, Depression accounts for approximately 70% of the dataset, while Confusion represents nearly 20%, with the remaining categories collectively comprising less than 10%. This proportional distribution highlights the concentration of negative emotional states within the discourse.

The statistical results reported below the chart ($\chi^2 = 15140.00$, dof = 5, $p < 0.001$) indicate that the observed distribution of emotional categories significantly deviates from an expected uniform distribution. This confirms that the dominance of particular emotional states is not attributable to random variation. In conclusion, the POMS-based emotion profiling reveals a public discourse overwhelmingly characterized by Depression and Confusion, with a smaller yet notable presence of Anger and other negative emotional states, and a minimal representation of positive affect such as Vigour.

Several limitations should be acknowledged. The dataset is derived from a single YouTube video, which may not represent the broader Indonesian population. YouTube commenters constitute a self-selected group and may exhibit stronger emotional expression than the general public. Automated text classification may also be affected by sarcasm, irony, and contextual nuances that are difficult to capture through lexicon-based or rule-based methods. Therefore, the findings should be interpreted as indicative patterns within this specific discourse context rather than definitive measures of nationwide sentiment.

CONCLUSION

The comprehensive analysis of public discourse surrounding the Indonesian bank account regulation has yielded a crucial and multi-layered conclusion that transcends the specific policy itself. This study, through its AI-driven analytical framework, mapped patterns within the emotional landscape of the Indonesian public, indicating a predominantly negative sentiment

distribution. The findings suggest that the public's reaction extended beyond simple policy disagreement and may reflect broader societal anxieties.

The quantitative data from the POMS analysis serves as the cornerstone of this conclusion. The overwhelming predominance of the Depression and Confusion scales, with counts of 2121 and 603 respectively, is the most salient finding. This pattern suggests that a substantial portion of public sentiment may be associated with feelings of hopelessness and uncertainty rather than predominantly confrontational anger. The high level of confusion further indicates a fundamental breakdown in communication; the public does not understand the rationale or the practical implications of the policy, which breeds fear and distrust. These quantitative results are not isolated data points but are directly validated by the qualitative findings. The word cloud and topic modeling analysis consistently highlighted themes of economic hardship ("nganggur," "miskin"), systemic corruption ("koruptor," "pejabat," "maling"), and the perceived injustice of a policy that targets ordinary citizens while a lack of accountability for the powerful persists. Comments like "Negara sakit" (a sick country) and "ini indonesia makin parah rampok baru" (Indonesia is getting worse, new thieves) perfectly encapsulate the deep depression and disillusionment identified by the POMS model.

This research suggests that the PPATK regulation may have functioned as a trigger within an existing climate of frustration and economic insecurity. The public reaction may reflect broader concerns regarding institutional trust and economic vulnerability. However, these findings should be interpreted within the boundaries of the dataset, which is derived from a single high-engagement YouTube video and may not fully represent the broader Indonesian population. While the emotional patterns identified are statistically significant within this corpus, further multi-platform and longitudinal studies would be necessary to establish wider generalizability. The collective feeling of being unheard and unprotected against both economic threats and official overreach transformed a regulatory discussion into a symbolic battle for economic justice. The study suggests that the AI-driven analytical framework can offer insights beyond basic sentiment polarity by mapping differentiated emotional states within public discourse. This approach provides an additional layer of interpretation for understanding societal mood, while further validation would strengthen its broader applicability.

The findings of this research carry significant implications across several domains: public policy, financial regulation, and the field of social science and AI. For policymakers in Indonesia, the primary takeaway is the need to incorporate structured emotion-based monitoring into the policy cycle, particularly at the stages of agenda-setting, communication design, and post-implementation evaluation. Rather than relying solely on approval ratings or formal feedback channels, policymakers could utilize emotion distribution indicators (e.g., dominance of Depression or Confusion) as early warning signals of communication gaps or legitimacy risks. For example, a high proportion of confusion-related discourse may indicate insufficient clarity in regulatory explanation, while elevated depression-related expressions may signal perceived economic vulnerability among affected groups. Integrating such indicators into digital monitoring dashboards could allow regulators to adjust messaging strategies, conduct targeted public outreach, or clarify regulatory provisions before distrust escalates. A policy's technical merit is insufficient if its human and emotional impact is neglected. The high scores on the Depression and Confusion

scales serve as a critical warning sign that the public is not merely against a regulation but is struggling with fundamental fears about their economic survival. Future policy initiatives, especially those concerning finance and personal assets, must be accompanied by a robust and empathetic communication campaign that not only explains the policy's purpose but also directly addresses public anxieties. Simply stating that a regulation is for the public good will not suffice; the government must transparently demonstrate how it will protect the most vulnerable and not serve as a tool of oppression. This study underscores that rebuilding public trust is an essential prerequisite for effective governance.

For banking and financial institutions, including PPATK, the implications are equally profound. The public's reaction reveals a critical gap in trust between these institutions and the people they are meant to serve. The public does not perceive PPATK's actions as a safeguard against money laundering but as a potential threat to their hard-earned savings. This has significant implications for financial inclusion, as a fearful public may choose to keep their money outside the formal banking system, which is detrimental to the broader economy. PPATK and other financial regulators must actively engage in public relations and community outreach to demystify their roles and build confidence. They need to shift their narrative from a purely regulatory one to one that emphasizes their role as protectors of the public's financial well-being. The findings suggest that a collaborative approach, perhaps involving public consultations and clearer, more accessible information, could mitigate future negative reactions.

Finally, this research offers a dual contribution. Methodologically, it demonstrates how an integrated AI-driven framework can structure large-scale digital discourse into interpretable thematic and emotional patterns. Beyond methodology, the study also contributes to governance theory by empirically illustrating how differentiated mood states particularly depression and confusion may signal forms of institutional distrust that differ from overt anger or opposition. This distinction refines theoretical understandings of policy legitimacy by suggesting that emotional governance involves not only managing visible dissent but also addressing underlying affective states associated with vulnerability and uncertainty. By linking emotion analytics to questions of trust and legitimacy, the study extends the discussion from technical sentiment analysis to broader debates on emotional dimensions of democratic governance. It provides an illustrative case study demonstrating how integrated AI-based techniques can be applied to policy-related digital discourse analysis. The application of the POMS-based framework in this context highlights its potential for differentiating nuanced emotional states beyond basic polarity scoring. The methodology developed in this study can be a template for future research on online political discourse, public health crises, and sociological trends in other contexts. It opens up new avenues for scholars to monitor and understand public sentiment in real-time, providing a vital bridge between the digital world and real-world policy implications. Moving forward, the research community should continue to refine these models to better capture cultural and linguistic nuances, further refining their interpretive robustness in diverse linguistic and cultural contexts. This study suggests that AI-based analytical approaches can contribute to deeper interpretive understanding of digital public discourse when applied with appropriate methodological caution. Beyond methodological refinement, the findings also intersect with governance legitimacy frameworks by illustrating how differentiated emotional states such as depression and confusion

may signal latent vulnerabilities in institutional trust that are not captured through approval-based metrics alone. In this sense, emotion-based digital analysis can complement existing legitimacy theories by providing empirically grounded insight into affective dimensions of policy reception within contemporary democratic governance.

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