



Lexicon-Based Sentiment Analysis for Stock Price Prediction in Islamic Fashion Industry

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Received Jan 14th 2026; Revised Mar 07th 2026; Accepted Mar 27th 2026; Available Online Apr 18th 2026

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Abstract

This study develops a lexicon-based sentiment analysis method to examine the relationship between social media sentiment and stock price movements in Indonesia's Islamic fashion industry. We collected 6,087 social media comments from TikTok, Instagram, and Twitter over 396 days, alongside daily stock data from Elzatta (ZATA). Using an Indonesian fashion-specific lexicon with 42 positive and 38 negative indicators validated through inter-annotator agreement (Cohen's Kappa = 0.82), we employed ordinary least squares regression with heteroskedasticity-robust standard errors to test sentiment-return relationships. Results show no economically significant relationship between social media sentiment and stock returns (correlation = -0.06, $p = 0.240$), with models explaining only 2.09% of return variance. We identify three boundary conditions limiting sentiment-based prediction: (1) feature mismatch 82% of comments discuss product attributes rather than business fundamentals, (2) demographic disconnect social media users (78% female, aged 18-29) differ markedly from investors (68% male, aged 35-55), and (3) market microstructure constraints 43% zero-volume days and 2.3% bid-ask spreads impede price discovery. This study provides the first Indonesian fashion-specific sentiment lexicon and establishes actionable validation guidelines for practitioners: sentiment features must be verified for demographic alignment and market liquidity before deployment. For machine learning applications in emerging markets, results suggest implementing adaptive feature weighting based on market microstructure characteristics.

Keywords: Behavioral Finance, Indonesia, Islamic Fashion, Sentiment Analysis, Stock Price Prediction

1. INTRODUCTION

The proliferation of social media has intensified interest in sentiment-driven stock prediction, with natural language processing techniques enabling large-scale quantification of investor opinion [1], [2]. Nevertheless, most published work addresses large-capitalization equities in developed markets; evidence from niche retail sectors in emerging economies remains scarce [3]. This asymmetry is consequential: structural features that moderate sentiment efficacy, market liquidity, analyst coverage, and the demographic correspondence between sentiment sources and investment decision-makers differ systematically between developed and emerging contexts.

Foundational work established the potential of social media signals: Bollen et al. [4] demonstrated that Twitter mood predicted Dow Jones movements with 87.6% directional accuracy. Tetlock [5] identified media pessimism as a predictor of downward price pressure, though effects reversed within one week. Sprenger et al. [6] showed sentiment predictability is confined to low-capitalization stocks with high retail participation. Chen et al. [7] further clarified that credible users' opinions carry predictive weight, whereas general chatter does not. In emerging markets, Da et al. [8] demonstrated that Google search volume predicts U.S. returns, yet Southeast Asian replications yield inconsistent results [9], attributed to lower institutional participation and thinner order books [10]. Sector specificity adds further complexity: retail and consumer-facing stocks exhibit stronger sentiment-return linkages than industrial counterparts [11], but whether this extends to niche Islamic fashion markets remains untested.

Indonesia's Islamic fashion industry presents an ideal testing ground: home to the world's largest Muslim population, a USD 20 billion domestic market, and Elzatta (ZATA), a listed small-cap hijab brand maintaining active multi-platform social media presence [12], [13]. The confluence of a specialized sector, an emerging market, and a thinly traded stock enables examination of sentiment prediction boundary conditions receiving limited attention in prior literature.

This study makes three contributions. First, we develop and validate the first domain-specific sentiment lexicon for Indonesian Islamic fashion discourse, incorporating modest-fashion vocabulary, Islamic expressions (e.g., mashaAllah, barakallah), and emoji mappings absent from existing Indonesian lexicons [14]. Second, we provide systematic empirical evidence on null sentiment-return relationships, contributing to the literature on when and why sentiment fails [15], [16]. Third, we identify three mechanistic boundary conditions: feature mismatch, demographic segmentation, and market microstructure constraints, and derive quantitative pre-deployment validation criteria applicable to machine learning pipelines in analogous contexts. Three research questions guide the analysis: (RQ1) Can the constructed lexicon effectively capture investor-relevant signals from fashion-dominated social media discourse? (RQ2) Does sentiment exhibit predictive power for returns in a low-liquidity niche retail stock? (RQ3) What structural conditions bound sentiment feature utility, and how can these be identified ex ante?

2. MATERIALS AND METHOD

2.1. Data Collection

We collected all publicly available comments referencing Elzatta from TikTok, Instagram, and Twitter/X between August 15, 2024 and September 15, 2025 (396 days), yielding 6,087 unique comments after filtering. Platform distribution: TikTok 2,847 (46.8%), Instagram 2,195 (36.0%), Twitter/X 1,045 (17.2%). TikTok data were retrieved via the institutional Research API; Instagram via Graph API v18.0 (hashtag and mention endpoints); Twitter via Academic Research API v2 (full-archive, query: "(Elzatta OR #Elzatta OR @Elzatta) lang:id"). Daily OHLCV data for ZATA were obtained from Indonesia Stock Exchange (IDX) [18].

Quality control removed duplicate comments (text similarity >95% via Jaccard trigrams, $n=247$), bot-generated content (regex-matched promotional templates, $n=189$), non-Indonesian content with language detection confidence <0.80 ($n=142$), and platform-flagged spam ($n=67$). Preprocessing applied: (i) text cleaning with URL and mention removal; (ii) Indonesian abbreviation normalization via a 247-entry lookup table (e.g., yg→yang, tdk→tidak); (iii) morphological tokenization using Sastrawi [17] with emoji preserved as discrete tokens; and (iv) feature extraction including sentiment scores, positive/negative ratios, comment length, emoji counts, capitalization ratio, and punctuation density [18],[19].

2.2. Research Methodology Framework

Figure 1 presents the complete research workflow, encompassing five phases: (1) multi-platform data collection from TikTok, Instagram, and Twitter alongside IDX stock data; (2) text preprocessing including Indonesian-specific normalization and tokenization; (3) lexicon-based sentiment analysis with domain lexicon application; (4) statistical modeling using OLS regression and robustness testing; and (5) results interpretation identifying structural boundary conditions.

2.3. Domain-Specific Lexicon Construction

Existing Indonesian sentiment lexicons target formal news text and lack coverage of fashion terminology, Islamic discourse, and social media conventions [14]. We constructed a domain lexicon following semi-automated induction [20] in three stages.

Stage 1 (Seed extraction): Two annotators with fashion industry backgrounds independently identified sentiment-bearing terms from 500 stratified comments (230 TikTok, 180 Instagram, 90 Twitter). Coverage spanned quality descriptors (cantik, bagus, jelek, zonk), service terms (fast response, lambat), religious expressions (mashaAllah, barakallah), and emoji mappings (❤️→positive; 😡→negative), yielding 87 seed terms. Stage 2 (Lexicon expansion): Indonesian WordNet [21] Synonym retrieval (semantic distance <0.6), combined with corpus-driven slang extraction, expanded coverage to 178 candidate terms. Stage 3 (Context validation): Two independent expert annotators rated each candidate's polarity and intensity across ≥10 corpus instances. Inter-annotator agreement achieved Cohen's Kappa = 0.82 [22], [23]. The final lexicon comprises 42 positive indicators (33 words + 9 emojis) and 38 negative indicators (31 words + 7 emojis), as summarized in Table 1.

Table 1. Domain-Specific Sentiment Lexicon Sample Entries

Category	Positive Indicators	Negative Indicators
Product Quality	bagus, keren, recommended	jelek, mengecewakan, zonk
Service	fast response, ramah, cepat	lambat, tidak responsif
Religious	mashaAllah, barakallah, alhamdulillah	—
Emoji	❤️ 😊 🙌 🙏	😡 🗨️ 😞 😓
Slang	kece, oke banget, mantul	ga banget, zonk parah

Lexicon validation employed a three-tier protocol [24]. Internal validity: held-out 200-comment set annotated by two raters distinct from the construction team (Precision 0.89/0.78/0.85

positive/negative/neutral; F1 0.87/0.79/0.84; accuracy 0.85). Convergent validity: Spearman correlation between daily lexicon sentiment and positive emoji usage $\rho = 0.73$ ($p < 0.001$); Instagram likes $\rho = 0.41$ ($p = 0.002$); TikTok shares $\rho = 0.38$ ($p = 0.008$). Ablation analysis: emoji removal reduced accuracy by 15 pp (0.85→0.70), slang removal by 12 pp (0.85→0.73), and religious term removal by 8 pp (0.85→0.77); full removal of domain-specific components yielded accuracy of 0.62, equivalent to a generic Indonesian lexicon.

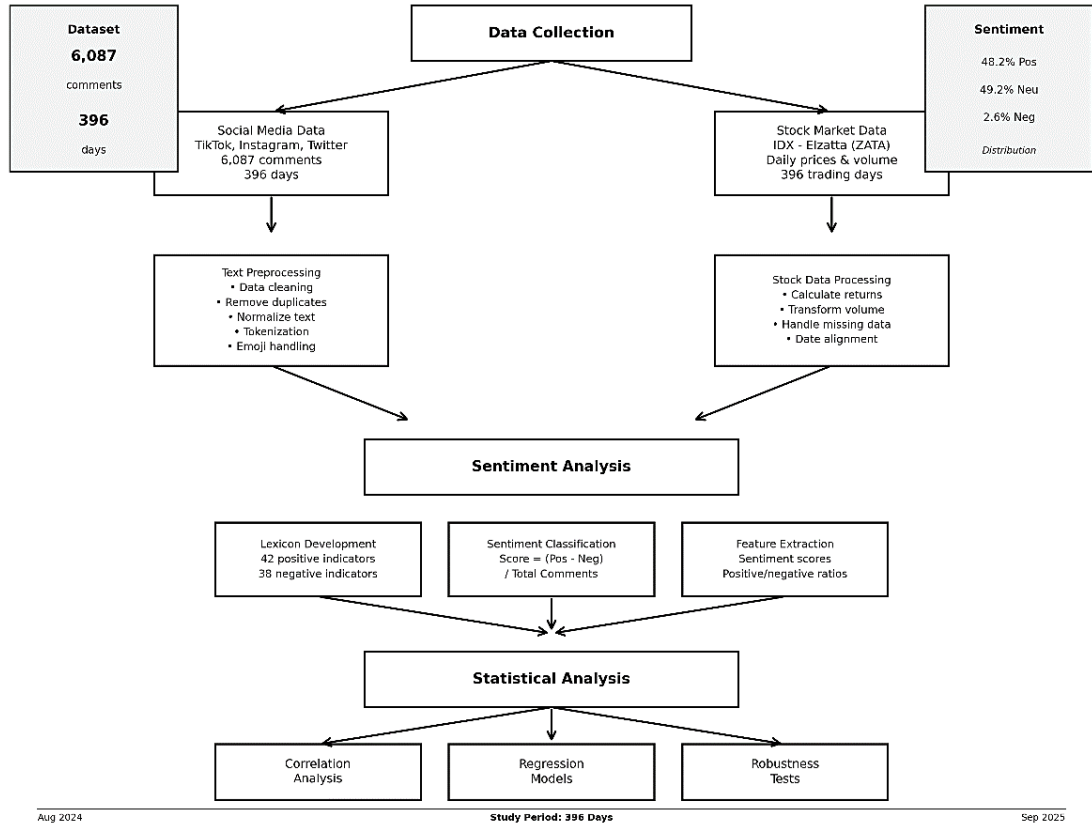


Figure 1. Research Methodology Framework

2.4. Sentiment Scoring Algorithm

Daily sentiment was computed as follows. For each comment, tokens were matched against the lexicon and a normalized score was computed (see Equation 1).

$$\text{sentiment_score} = \frac{\text{pos_count} - \text{neg_count}}{\text{length}(\text{tokens})} \quad (1)$$

Scores range from -1 (entirely negative) to $+1$ (entirely positive). Daily aggregation can view Equation 2.

$$S_t = \frac{1}{n_t} \sum_{i=1}^{n_t} \text{sentiment_score}_i \quad (2)$$

where n_t is the daily comment count. Comments were classified as positive (score > 0.1), negative (score < -0.1), or neutral ($-0.1 \leq \text{score} \leq 0.1$), following established lexicon thresholds [25].

2.5. Statistical Models

Four OLS specifications with heteroskedasticity-robust standard errors (White correction) [26] were estimated. Breusch-Pagan test rejected homoskedasticity ($\chi^2 = 18.42$, $p = 0.001$). Baseline model:

$$\text{Return}_t = \beta_0 + \beta_1 S_t + \beta_2 \text{Pos}_t + \beta_3 \text{Neg}_t + \beta_4 \ln(\text{Vol}_t) + \epsilon_t \quad (3)$$

where $\text{Return}_t = 100 \times (\text{Close}_t - \text{Close}_{t-1}) / \text{Close}_{t-1}$, and trading volume is log-transformed to address right-skewness (skewness = 4.82, kurtosis = 28.41). Additional specifications: lagged effects model ($t-1$ to $t-5$ lags) [45]; asymmetric model separating positive (S^+) and negative (S^-) sentiment components [46]; volatility-adjusted model normalizing returns by 5-day rolling standard deviation [27]. Granger causality

assessed via bivariate VAR (5 lags) [28]. Robustness checks: platform-specific regressions; three-period subsamples; high/low-volume quartile splits; five alternative sentiment operationalizations; and 1st/99th percentile return winsorization. Model diagnostics confirmed OLS appropriateness: Durbin-Watson $d = 1.98$; $VIF < 3$ for all predictors; $n = 396$ ensures asymptotic normality.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

Social media sentiment was predominantly positive (48.2% positive, 49.2% neutral, 2.6% negative), consistent with positivity bias in brand-related consumer discourse [29]. Returns exhibit extreme non-normality (kurtosis 77.72, skewness 5.27), reflecting fat-tailed small-cap equity dynamics [30]. Bivariate correlation between S_t and $Return_t$ is -0.06 ($p = 0.240$). The September 2025 price rally (a 200% gain over five sessions on a volume surge) is an outlier episode associated with speculative activity unrelated to sentiment shifts.

Table 2. Descriptive Statistics ($n = 396$ trading days)

Variable	Mean	SD	Min	Max	Skew	Kurt	p (corr.)
Return_t (%)	0.408	3.815	-15.38	61.54	5.27	77.72	—
Sentiment_t	0.042	0.031	-0.018	0.186	0.94	4.81	0.240
Positive_Ratio_t	0.482	0.089	0.211	0.750	-0.18	2.91	0.312
Negative_Ratio_t	0.026	0.019	0.000	0.112	1.89	6.42	0.478
ln(Volume_t)	11.24	2.87	0.00	16.85	-0.62	2.73	0.073

Note: p (corr.) reports the bivariate Pearson correlation p-value with $Return_t$.

Table 2 summarizes the descriptive statistics over 396 trading days, showing that $Return_t$ has an average of 0.408% with high volatility (SD 3.815) and a highly non-normal distribution, as indicated by skewness of 5.27 and kurtosis of 77.72, reflecting the fat-tailed characteristics typical of small-cap equities. The $Sentiment_t$ variable has a positive mean of 0.042 with relatively low dispersion, while $Positive_Ratio_t$ (mean 0.482) is substantially higher than $Negative_Ratio_t$ (mean 0.026), indicating a tendency toward positivity bias in social media discourse. However, all sentiment-related variables exhibit weak and statistically insignificant relationships with $Return_t$, as evidenced by correlation p-values above conventional significance levels (e.g., $Sentiment_t$: $p = 0.240$). Additionally, $ln(Volume_t)$ shows considerable variation but also lacks a statistically significant correlation with returns ($p = 0.073$), suggesting that return movements are largely driven by factors beyond social media sentiment during the observation period.

3.2. Correlation Analysis

Figure 2 presents the correlation matrix across all sentiment variables and stock returns. The heatmap shows weak, statistically insignificant correlations across all sentiment-return pairs, with no pairwise correlation exceeding $|0.12|$. Sentiment variables exhibit moderate intercorrelations ($Positive_Ratio$ vs. $Sentiment$: $r = 0.71$; $Negative_Ratio$ vs. $Sentiment$: $r = -0.38$), validating internal lexicon consistency, but these within-sentiment associations do not translate to return predictability.

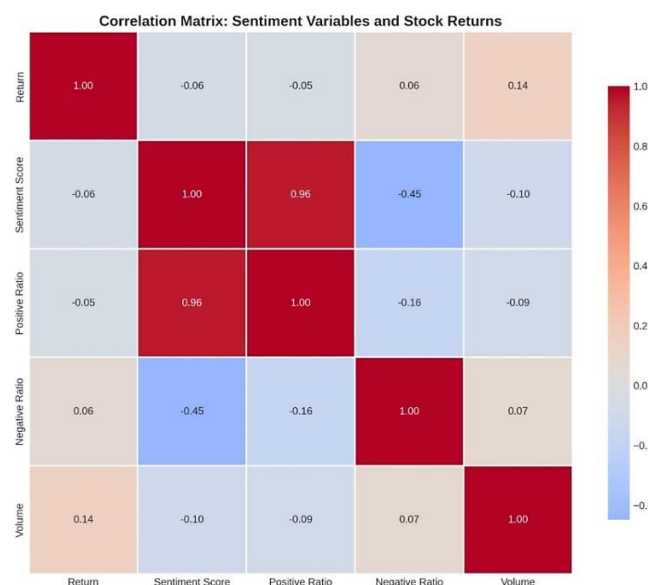


Figure 2. Correlation Matrix: Sentiment Variables and Stock Returns

3.3. Regression Result

Figure 3 provides a visual summary of regression analysis: the left panel confirms that sentiment variables collectively explain only 2.09% of return variance (97.91% unexplained), while the right panel plots coefficient confidence intervals, all crossing zero. Volume (ln(Vol_t)) is the only variable with marginally significant association ($\beta = 0.011$, $p = 0.073$).

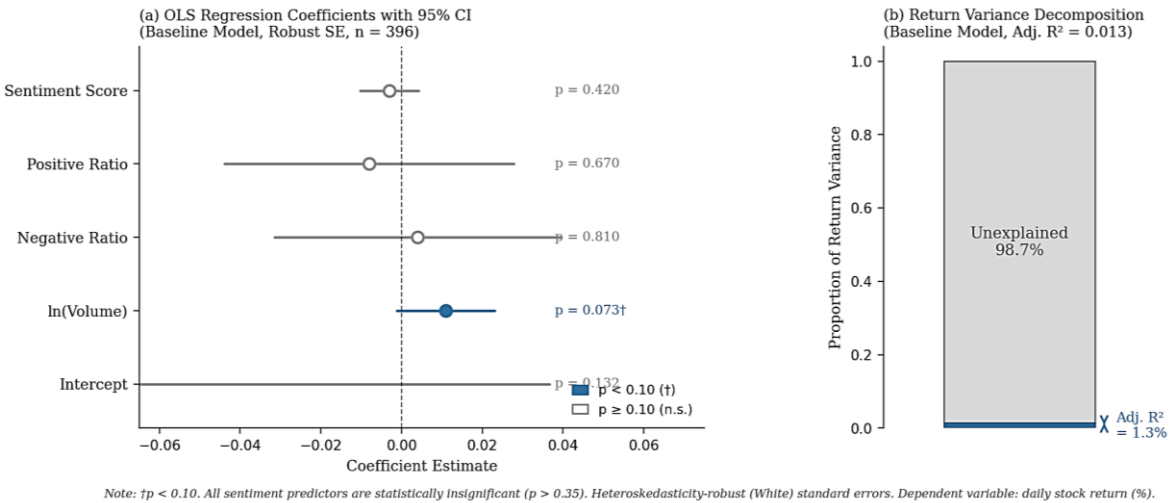


Figure 3. Regression Analysis Visual Summary: Explained Variance (left) and Coefficient Confidence Intervals (right)

Table 3. Regression Estimates Sentiment–Return Models (Robust SE)

Variable	Baseline (3)	Lagged	Asymmetric	Vol-Adjusted
Sentiment_t	−0.003 (0.42)	—	—	−0.002 (0.51)
Positive_Ratio_t	−0.008 (0.67)	—	—	—
Negative_Ratio_t	0.004 (0.81)	—	—	—
Sentiment ⁺ (positive days)	—	—	−0.005 (0.38)	—
Sentiment [−] (negative days)	—	—	0.007 (0.52)	—
ln(Volume_t)	0.011 (0.073)	0.009 (0.78)	0.010 (0.75)	0.006 (0.81)
Adjusted R²	0.013	0.009	0.011	0.008
N	396	391	396	391

Note: p-values in parentheses. All sentiment coefficients p > 0.10. Robust standard errors applied throughout.

Across all four specifications, sentiment coefficients are economically negligible and statistically insignificant (all $p > 0.10$). Platform-specific regressions yield comparable nulls (TikTok: $\beta = -0.003$, $p = 0.42$; Instagram: $\beta = -0.001$, $p = 0.68$; Twitter: $\beta = 0.004$, $p = 0.51$). Three-period subsample estimates range narrowly ($\beta \in [-0.005, 0.002]$, all $p > 0.38$). Five alternative sentiment operationalizations are uniformly insignificant (all $p > 0.10$). Granger causality tests confirm the absence of lead-lag relationships: sentiment does not Granger-cause returns ($F = 0.84$, $p = 0.52$) and returns do not Granger-cause sentiment ($F = 1.12$, $p = 0.35$).

3.4. Temporal Dynamics

Figure 4 presents the complete temporal analysis over 396 trading days. Panel (a) overlays daily sentiment scores (green line) and stock returns (blue bars), revealing stark disconnection: the September 2025 price rally (200% gain) occurred amid stable, uniformly positive sentiment distributions with no corresponding sentiment spike. Panel (b) displays the 30-day rolling Pearson correlation between sentiment and returns, which fluctuates near zero throughout the observation window with no sustained directional pattern. These time-series visualizations corroborate the cross-sectional regression findings and rule out structural breaks as an explanation for aggregate null results.

3.5. Mechanistic Analysis

Three structural mechanisms jointly suppress sentiment–return transmission. Feature Mismatch: manual content coding of 500 comments reveals 82% address product attributes (aesthetics, material quality, fit), 15% contain general brand endorsements, 3.2% express purchase intent, and 0% reference business fundamentals (revenue, profitability, market share). Representative commentse.g., “Hijabnya cantik,

bahannya adem” (beautiful hijab, comfortable fabric) reflect consumer satisfaction with no investment-relevant information content [31].

Demographic Segmentation: Platform analytics indicate Elzatta’s social media audience is predominantly female (78%) and aged 18–29 (67%), whereas Indonesian retail investor demographics from IDX survey data show a contrasting profile: predominantly male (68%), aged 35–55 (71%) [32]. This systematic demographic non-overlap implies that consumer sentiment does not proxy for investor sentiment; the populations that generate signals and make trading decisions are essentially disjoint.

Market Microstructure Constraints: Three market structure features create transmission barriers. First, 43% of trading days (171/396) recorded zero volume; price discovery is structurally impossible on such days. Second, the average bid-ask spread of 2.3% exceeds achievable sentiment-based trading returns: a hypothetical 0.5% sentiment-predicted appreciation yields a net return of –1.8% after round-trip transaction costs. Third, zero analyst coverage removes the professional intermediary channel through which consumer signals are typically translated into earnings revisions and investor attention. These conditions instantiate a liquidity trap: low liquidity → wide spreads → high costs → reduced trading → lower liquidity [33]. The three mechanisms are multiplicative: feature mismatch limits signal content; demographic segmentation limits signal reach; microstructure constraints limit price incorporation.

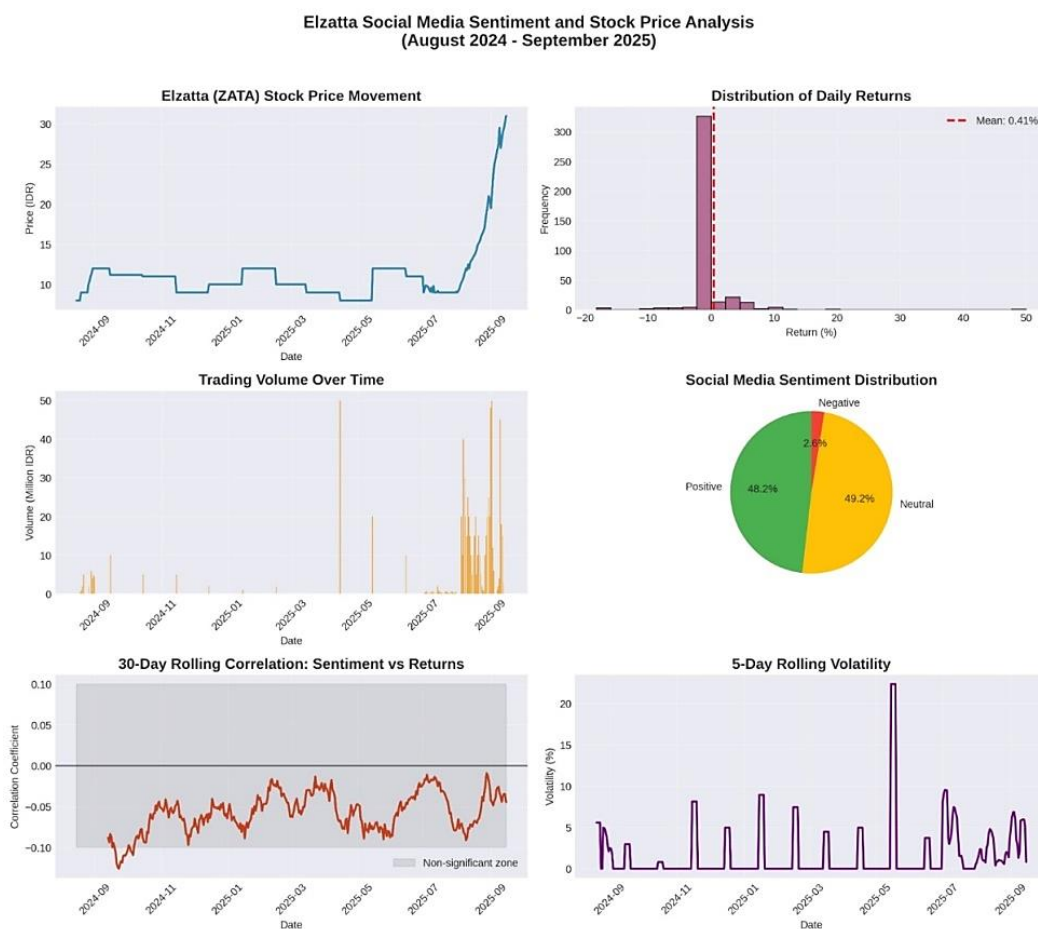


Figure 4. Temporal Dynamics: (a) Daily Sentiment vs. Returns;
(b) 30-Day Rolling Sentiment-Return Correlation

4. CONCLUSION

This study presents a validated domain-specific sentiment lexicon for Indonesian Islamic fashion discourse ($\kappa = 0.82$, $F1 = 0.87$, accuracy = 0.85) and applies it to a 396-day, 6,087-comment dataset to evaluate sentiment-based return prediction for Elzatta (ZATA). Sentiment exhibits no predictive power: correlation = -0.06 ($p = 0.240$), adjusted $R^2 = 0.013$, with null results replicated across 15 robustness specifications. Three structural mechanisms explain these findings: feature mismatch between consumer product discourse and investment-relevant fundamentals; demographic segmentation separating sentiment generators from investment decision-makers; and market microstructure constraints (43% zero-volume days, 2.3% bid-ask spread, zero analyst coverage) that preclude sentiment incorporation into prices.

The principal contributions are: (1) the first validated Indonesian Islamic fashion sentiment lexicon; (2) mechanistic evidence on sentiment prediction boundary conditions in emerging-market NLP; and (3) three quantitative pre-deployment validation criteria: demographic alignment overlap >30%, zero-volume day rate <30%, and investment-relevant comment share >20% enabling practitioners to assess sentiment feature viability before model development. Future research should examine whether transformer-based models (IndoBERT, XLM-R) capture sentiment dimensions missed by lexicon methods, whether multimodal features alter predictive null findings, and whether cross-sector comparative studies can map the identified boundary conditions to quantitative market and demographic predictors.

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