



Economic Pragmatism over Religious Normativity: A Sentiment, Argument, and Emotion Analysis of Indonesian Muslim Discourse on Buy-Now-Pay-Later Services

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Article Info	Abstract
Article history: Received March 10, 2026 Revised April 13, 2026 Accepted June 27, 2026 Available online August 15, 2026 *Corresponding author email: i000190080@student.ums.ac.id Keywords: Buy-Now-Pay-Later, digital religion, framing, Indonesian Muslims, Islamic finance.	Introduction/Main Objectives: his study examines the factors influencing Islamic microfinance adoption intention among Micro, Small, and Medium Enterprises (MSMEs) in Malang City, focusing on Islamic financial literacy, Shariah attitude, and technology readiness. Research Methods: A quantitative approach with a causal-explanatory design was employed. The study involved 200 MSME owners or managers as respondents. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. Finding/Results: The results show that Islamic financial literacy, Shariah attitude, and technology readiness have positive and significant effects on Islamic microfinance adoption intention. Islamic financial literacy is the most dominant factor, while the proposed model explains 44.1% of the variance in adoption intention. These findings indicate that adoption intention is influenced by financial knowledge, Shariah-oriented values, and digital readiness. Conclusion: Islamic microfinance adoption is driven by financial literacy, Shariah attitude, and technology readiness.
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INTRODUCTION

Buy Now Pay Later (BNPL) services have transformed the Indonesian fintech market. By the third quarter of 2024, the country's eight regulated BNPL providers had disbursed more than IDR 30 trillion in outstanding receivables, with over 23 million active users, the majority under 35 years old (Otoritas Jasa Keuangan, 2024). Embedded inside the checkout flow of every major e-commerce platform, BNPL operates as a frictionless credit instrument: a single tap converts a purchase into installments that carry a monthly markup, typically between 1.75% and 4.4% (Bank Indonesia, 2023). For the world's largest Muslim population, this raises a religiously charged question, because that markup, in the language of Islamic jurisprudence, is a candidate for *ribā*. *Ribā*, the predetermined increment paid on a loan in addition to its principal, is one of the most explicit prohibitions in classical Islamic law (Q. 2:275–279; El-Gamal, 2006; Iqbal & Mirakhor, 2011). However, the everyday adoption of BNPL among Indonesian Muslims has run far ahead of any settled communal interpretation. National religious authorities have issued cautious advisories rather than blanket fatwas (Majelis Ulama Indonesia, 2022), while sharia-compliant alternatives such as *qarḍ* or *murābahah* remain absent from the dominant e-commerce checkout flows. The space between formal religious doctrine and routine consumer practice has, as a result, been filled by ordinary users themselves, who debate the issue on the platforms where the transaction is made: TikTok and Instagram.

Recent scholarship has begun to map how Muslim consumers negotiate digital finance, but it has done so largely through survey instruments (Souiden & Rani, 2015; Mokhlis, 2009), in-depth interviews (Slama, 2018; Nisa, 2018), or single-platform sentiment analysis of formal Islamic banking (Razouk et al., 2023; Arif Lubis, 2024). Three gaps remain. First, studies of BNPL have focused on its economic and behavioral antecedents (Aalders, 2023; Gerrans et al., 2022; Johnson et al., 2021), leaving the religious controversy under-examined. Second, sentiment analysis in the Islamic finance space has rarely been combined with frame analysis, so we know how positive or negative the discourse is, but not what arguments organize that polarity (Cambria et al., 2017). Third, comparative work across short-form video and image-based platforms is scarce, despite evidence that platform affordances reshape the kind of religious talk users produce (Bhandari & Bimo, 2022; Highfield & Leaver, 2016).

This article addresses those gaps with a content-analytic sentiment study of 547 user comments collected from TikTok and Instagram posts discussing *ribā* and BNPL between November 2022 and September 2025. The study has four research questions:

RQ1: How is sentiment toward *ribā* and BNPL distributed in Indonesian Muslim social-media discourse?

RQ2: What argument frames (economic, religious, critical, emotional) dominate the discourse, and how are they distributed across sentiment?

RQ3: Is there a structural association between argument frame and sentiment, and which combinations are over- or under-represented?

RQ4: How do TikTok and Instagram differ in the sentiment and frames they host?

RQ5: To what extent do argument frame, emotional intensity, and misinformation predict positive sentiment?

The study's contribution is fourfold. (i) Empirically, it provides the first quantitative mapping of how Indonesian Muslim publics frame BNPL in religious terms on the two platforms where most of that conversation happens. (ii) Methodologically, it integrates sentiment, frame, intensity, and misinformation coding in a single analytical pipeline, then submits the resulting variables to inferential tests rather than stopping at descriptive percentages, as much sentiment work in the Islamic-finance literature has done. (iii) Theoretically, it shows that economic framing, not religious framing, organizes the bulk of everyday Muslim talk about a religiously contested product, which has implications for the dual-process and behavioral-Islamic-finance literatures. (iv) Practically, it suggests that Sharia financial literacy interventions that rely on prohibitionist messaging are mis-targeted, because the audience is already discussing the issue through the economic frame. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on ribā, BNPL, framing, and digital religion, and states the working hypotheses. Section 3 describes the data, coding scheme, and analytical procedures. Section 4 reports descriptive and inferential results. Section 5 discusses the findings in relation to the prior literature and draws theoretical and practical implications. Section 6 concludes. Section 7 sets out limitations and directions for further research.

Literature Review and Theoretical Framework

Ribā and Its Contested Boundaries in Contemporary Islamic Finance

The prohibition of ribā is among the most strongly worded directives in the Qur'an, condemned in four separate passages (Q. 2:275–279; 3:130; 4:161; 30:39) and amplified in the Sunna (Iqbal & Mirakhor, 2011). Classical jurisprudence partitions the prohibition into two categories: ribā al-faḍl (excess in commodity exchange) and ribā al-naṣī'a (excess attached to deferred repayment), with the latter mapping most directly onto modern interest-bearing credit (Kamali, 2008; El-Gamal, 2006). Chapra (2008) and Khan (2010) argue that the prohibition is not a procedural rule but a substantive injunction against the rentier economy, intended to prevent the systematic transfer of risk and surplus from borrowers to lenders.

Contemporary scholarship, however, is divided on how the prohibition should be operationalized in retail digital finance. One stream, following Usmani (2002) and the AAOIFI standards, holds that any fixed premium on a loan, whatever its label, falls within ribā al-naṣī'a. A second stream, drawing on maqāṣid al-sharī'ah, distinguishes between exploitative compounding interest and modest service fees that preserve real purchasing power (Auda, 2008; Dusuki & Abdullah, 2007). BNPL sits awkwardly between these positions. Its monthly markup is small in absolute terms. However, it is fixed in advance, contractually enforceable, and increases

automatically on late payment, which moves it close to the classical definition of *ribā al-nasī'a* (Harahap et al., 2025).

In Indonesia, the Majelis Ulama Indonesia (MUI) has issued Fatwa No. 116/DSN-MUI/IX/2017 on electronic money and Fatwa No. 117/DSN-MUI/II/2018 on information-technology-based financing services, both of which require interest-free structures, but neither directly addresses the consumer-side BNPL flow operated by non-sharia providers. The interpretive gap is therefore not closed at the level of doctrine; it is being negotiated, comment by comment, by ordinary users on the platforms where the transaction takes place.

Buy-Now-Pay-Later: Behavior, Adoption, and the Religious Question

BNPL has been studied predominantly as a behavioral and regulatory phenomenon. Gerrans, Baur, and Lavagna-Slater (2022) found that Australian BNPL users are disproportionately young, financially stressed, and prone to impulse purchasing. Johnson, Rodwell, and Hendry (2021) showed that BNPL users in the United Kingdom understate the credit-like nature of the product, treating it as a payment method rather than a debt. Aalders (2023) traced how platform design, especially the placement of the BNPL option above the cash option in checkout, increases uptake.

In the Indonesian context, the small but growing literature has focused on adoption drivers (Yusuf et al., 2023), credit-default behavior (Wahyudi & Sari, 2024), and the regulatory framework issued by Otoritas Jasa Keuangan. The religious dimension has been treated as a secondary variable, usually proxied by self-reported religiosity scores rather than analyzed as a discursive object (Souiden & Rani, 2015; Mokhlis, 2009). Harahap et al. (2025), in one of the few studies to center the religious question, conclude that millennial users justify BNPL through a hierarchy of necessity (*ḍarūrah*) arguments that effectively suspend the *ribā* prohibition for routine consumption. Our study takes that finding as a point of departure and asks whether the same justificatory pattern is evident in unsolicited social media discourse.

The behavioral economics literature suggests an interpretive frame. Thaler (2016) and DellaVigna (2009) document how present-biased preferences and mental accounting lead consumers to treat installment payments as smaller, separate transactions, thereby dulling the perception of the total cost. Tversky and Kahneman (1981) show that the framing of a financial decision, gain or loss, payment or saving, alters its acceptability. Applied to BNPL, the behavioral account predicts that the dominant frame in lay discourse will be economic-pragmatic rather than religious-normative, because the cost of switching frames is high and the immediate incentive structure rewards the economic frame.

Sentiment, Frame, and the Algorithmic Public Sphere

Sentiment analysis emerged in computational linguistics as the task of classifying the polarity of opinionated text (Pang & Lee, 2008; Liu, 2012). Its translation into social-science research has been productive but methodologically uneven (Mäntylä, Graziotin & Kuutila, 2018).

A recurring critique is that sentiment polarity alone is a thin description: two negative comments can be negative for entirely different reasons, and what matters analytically is the argument that organizes the sentiment (Cambria et al., 2017; Edelman et al., 2020).

Framing theory offers the missing layer. Entman (1993, p. 52) defines framing as the selection of “some aspects of a perceived reality” to make them more salient and to promote a particular interpretation. Chong and Druckman (2007) demonstrate that the frame chosen by communicators conditions audiences' evaluative responses. Applied to social media discourse, framing analysis asks not only whether a comment is positive or negative but also which interpretive register — economic, religious, critical, or emotional — it draws on. The intersection of sentiment and frame is, therefore, where descriptive polarity becomes a sociological object.

The algorithmic public sphere adds two further layers. Platform affordances shape which kinds of talk are rewarded with visibility (Bruns, 2019; Bhandari & Bimo, 2022). TikTok's short-video, quick-scroll architecture has been shown to favor spontaneous, hot-take responses (Vijay & Gekker, 2021). In contrast, Instagram's longer caption space and visual-first design encourage more reflective commentary (Highfield & Leaver, 2016). For religion specifically, Campbell's (2017) framework of mediated religion suggests that platform logic does not merely transmit religious content but reshapes the modes in which religious authority is exercised, contested, and ignored.

Misinformation has become a near-default concern in social-media research. Vosoughi, Roy, and Aral (2018) demonstrated that false stories spread faster than true ones on Twitter, while Pennycook and Rand (2019) showed that susceptibility is driven by inattention rather than ideological motivation. Lewandowsky, Ecker, and Cook (2017), however, argue that not all misinformation is consequential: low-stakes inaccuracies often coexist with accurate inferences. Whether this is true of Islamic finance discourse is an empirical question that this study takes up directly.

METHOD

Research Design

The study uses a quantitative content analysis design (Krippendorff, 2018; Neuendorf, 2017) applied to user-generated social media text. Content analysis was chosen because the research questions concern the manifest distribution of categories (sentiment, argument frame, emotional intensity, misinformation) in a defined corpus, and because the inferential techniques used here (chi-square, Kruskal–Wallis, Spearman, and binary logistic regression) require categorical or ordinal observations that can be hand-coded with adequate reliability. The unit of analysis is the individual user comment, defined as a single textual contribution posted in response to a creator's primary post. Replies to other comments were included if they made a substantive claim about BNPL or *ribā*; pure expressions of agreement without propositional content (“setuju”, “iya”) were excluded.

Data Collection

Comments were collected from four content creators, two on TikTok and two on Instagram, whose posts explicitly addressed the permissibility, mechanics, or controversy of BNPL services under Islamic law. The creators were selected through a two-step process. First, a search was conducted on each platform using the queries “paylater riba”, “paylater haram”, “paylater syariah”, and “BNPL Islam”, in both Indonesian and English. Second, posts with more than 500 comments and at least 10,000 likes were retained, and from this shortlist, the four most-engaged posts that explicitly framed BNPL through a religious lens were selected.

The collection window ran from 1 November 2022 to 30 September 2025, capturing the period from when BNPL passed 10 million Indonesian users (Otoritas Jasa Keuangan, 2022) to the most recent regulatory revision before data lock. After deduplication and removal of non-substantive replies, a final corpus of 547 comments was retained: 318 from TikTok and 229 from Instagram. The TikTok–Instagram ratio (1.39:1) is consistent with industry estimates of relative engagement on the two platforms for finance-related content in Indonesia (We Are Social & Meltwater, 2024).

Coding Scheme and Operationalization of Variables

Four variables were operationalized through a structured coding manual developed iteratively, with three pilot rounds conducted on a hold-out sample of 60 comments not included in the main corpus. Sentiment polarity was coded into three categories. Positive comments expressed support, approval, perceived benefit, or a favorable personal experience with BNPL or anti-ribā arguments. Negative comments expressed rejection, criticism, concern, or harm. Neutral comments were informative, hedged, or did not take a clear evaluative position.

The argument frame was coded into four mutually exclusive categories. Economic-frame comments grounded their position in financial cost, convenience, installment mechanics, or consumption need. Religious-frame comments grounded their position in Islamic law, the prohibition of ribā, ḥalāl/ḥarām status, or scriptural reference. Critical-frame comments offered rational evaluation, systemic critique, or analytic questioning of BNPL or its religious treatment. Emotionally framed comments expressed feelings (fear, anger, disappointment, enthusiasm) without articulated reasoning. Mixed cases were resolved by assigning the dominant frame; the second coder recoded ties (<3% of cases).

Emotional intensity was coded as an ordinal variable on a three-point scale. Low intensity covered comments that were calm, objective, or minimally emotional. Medium-intensity comments, covered with a discernible emotional charge, remained controlled. High-intensity comments with strong markers such as capitalization, repeated punctuation, or extreme lexical choices. Misinformation was coded as a binary variable. A comment was coded as containing misinformation if it included a factual claim that was either demonstrably false (e.g., misattributed Qur’anic verses), unverified speculation presented as fact, or a known fintech-related rumor debunked by official sources at the time of coding. Borderline cases were resolved

by consulting authoritative sources (MUI fatwa repository, OJK announcements, and peer-reviewed Islamic finance literature).

Inter-Coder Reliability

Two coders independently coded a random subsample of 110 comments (20.1% of the corpus). Cohen's kappa was calculated for each variable. Sentiment polarity reached $\kappa = 0.83$; argument frame $\kappa = 0.78$; emotional intensity $\kappa = 0.71$; misinformation $\kappa = 0.74$. All values exceed the 0.70 threshold recommended for content-analytic research (Krippendorff, 2018). Disagreements were resolved through structured discussion and, where unresolved, by a third coder.

Analytical Procedures

Analyses were carried out in Python 3.11 using pandas 2.1, SciPy 1.11 for non-parametric tests, statsmodels 0.14 for regression, and scikit-learn 1.3 for model diagnostics. Reproducibility was supported by storing all code and the deidentified coded dataset in a version-controlled repository (available on request). Descriptive analysis reported frequencies and percentages for each variable. Inferential analysis proceeded in four steps. First, a chi-square test of independence was used to test the association between argument frame and sentiment, with Cramér's V as the effect-size measure. Standardized residuals were calculated for each cell of the contingency table to identify which frame–sentiment combinations were over- or under-represented; residuals with an absolute value greater than 1.96 were treated as significant at the 5% level.

Second, a Kruskal–Wallis H-test compared emotional intensity across the three sentiment groups, with sentiment treated as the grouping variable and emotional intensity as the ordinal outcome. Spearman's rank-order correlation (ρ) measured the monotonic relationship between emotional intensity and sentiment polarity, with sentiment converted to an ordinal scale (negative = -1, neutral = 0, positive = +1).

Third, platform differences were tested using the Mann–Whitney U test for sentiment and emotional intensity and a chi-square test for argument frame, with TikTok versus Instagram as the grouping variable. A normalized cross-tabulation was used for visualization.

Fourth, a binary logistic regression model was estimated with positive sentiment (1 = positive, 0 = non-positive) as the outcome and argument frame, emotional intensity, and misinformation as predictors. Model fit was assessed through the Hosmer–Lemeshow test and Nagelkerke's pseudo- R^2 . Multicollinearity was assessed using variance inflation factors, all of which were below 2.0.

Hypotheses

The literature reviewed above motivates four working hypotheses, formulated to be testable against the data described in Section 3.

H1: Across the corpus, economic arguments will be more frequent than religious arguments, consistent with the behavioral prediction that everyday consumers default to the pragmatic frame for routine financial decisions.

H2: Argument frame and sentiment polarity will be significantly associated, with religious framing pulling toward positive sentiment (because it is invoked to defend a normative position) and critical or emotional framing pulling toward negative sentiment.

H3: Platform affordances will moderate discourse, with TikTok producing higher comment volume and more spontaneous economic framing, while Instagram produces a comparatively higher share of religious and reflective commentary.

H4: Argument frame and emotional intensity will predict positive sentiment in a multivariate model, while misinformation, given its low prevalence and benign character in this domain, will not.

RESULT AND DISCUSSION

RESULT

Descriptive Statistics (RQ1, RQ2)

The sentiment distribution across the 547 comments is reported in Figure 1 and Table 1. Neutral comments were the most frequent category ($n = 260$, 47.53%), followed closely by positive comments ($n = 247$, 45.16%); negative comments accounted for only 7.31% of the corpus ($n = 40$). The narrow gap between neutral and positive, set against the much smaller share of negative, indicates a discourse that is moderate rather than polarised. Public criticism of BNPL, where it appears, is concentrated in a small subset of comments rather than dispersed evenly through the corpus.

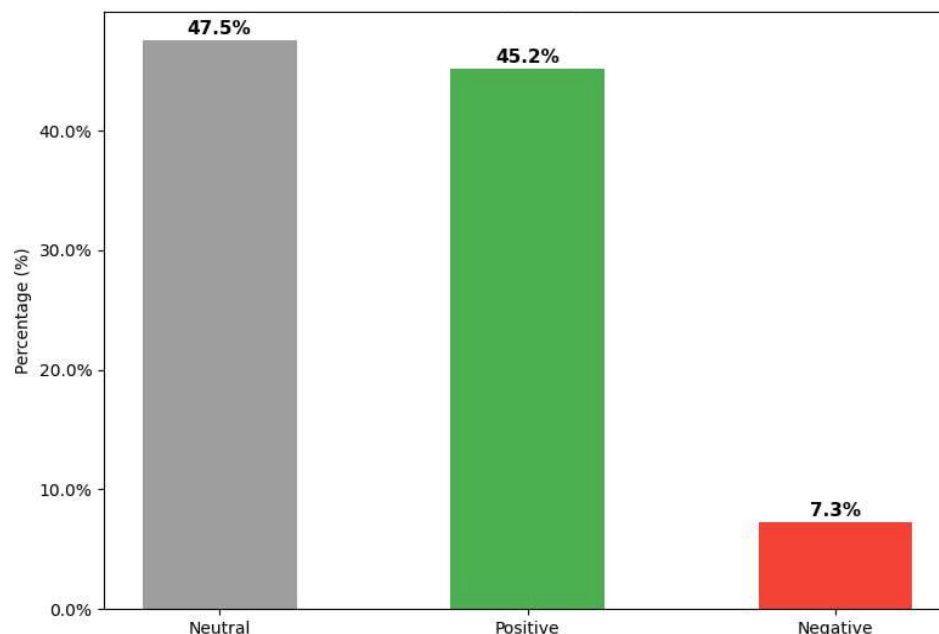


Figure 1. Sentiment distribution across the corpus (n = 547).

Argument-frame distribution is reported in Figure 2. Economic arguments dominated at 48.08% (n = 263), followed by religious arguments at 34.00% (n = 186). Critical (9.51%, n = 52) and emotional (8.41%, n = 46) framings remained marginal. The finding supports H1: in unsolicited discourse about a religiously contested financial product, the economic frame is more frequent than the religious frame by a ratio of approximately 1.41:1. Routine pragmatic reasoning, rather than scriptural reasoning, organizes most of the talk.

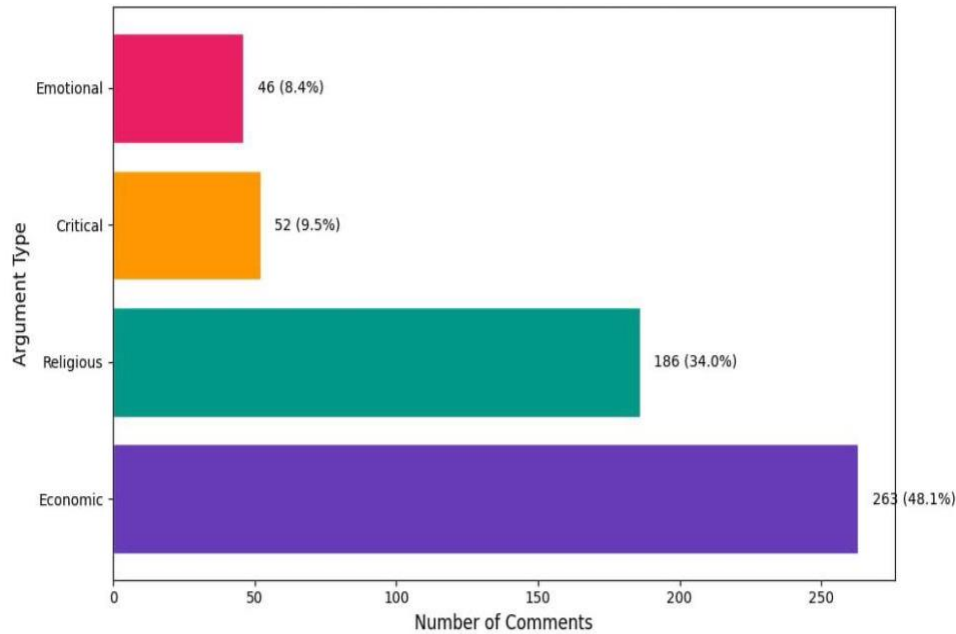


Figure 2. Frequency of argument types (n = 547).

Emotional intensity skewed strongly toward the low end. 64.90% of comments (n = 355) were coded as low-intensity, 29.80% (n = 163) as medium, and only 5.30% (n = 29) as high. Misinformation was rare: 96.89% of comments (n = 530) contained no identifiable misinformation, leaving 3.11% (n = 17) flagged. The distributions of all four variables are summarised in Table 1.

Table 1. Distribution of study variables (n = 547)

Variable	Category	Frequency (n)	Percentage (%)
Sentiment	Neutral	260	47.53
	Positive	247	45.16
	Negative	40	7.31
Argument frame	Economic	263	48.08

Variable	Category	Frequency (n)	Percentage (%)
Emotional intensity	Religious	186	34.00
	Critical	52	9.51
	Emotional	46	8.41
	Low	355	64.90
	Medium	163	29.80
	High	29	5.30
Misinformation	No	530	96.89
	Yes	17	3.11

Note. Percentages may not sum to exactly 100% due to rounding.

Argument–Sentiment Association (RQ3)

The relationship between argument frame and sentiment was tested with a 4×3 chi-square test of independence. The test returned $\chi^2 = 245.46$, $df = 6$, $p < .001$, with Cramér's $V = 0.474$, an effect size that falls in the medium-to-large range for a 4×3 design (Cohen, 1988). The result rejects the null hypothesis of independence and supports H2: argument frame and sentiment polarity are structurally associated.

The contingency table is shown in Figure 4. Economic-frame comments were distributed primarily into neutral ($n = 181$) and positive ($n = 74$) sentiment, with only 8 negative. Religious-frame comments were distributed sharply toward positive ($n = 151$), with 34 neutral and only 1 negative. Critical and emotional frames showed inverted patterns: critical-frame comments were concentrated in neutral ($n = 30$) and negative ($n = 14$) categories. In contrast, emotional-frame comments were the only category in which negative sentiment was modal ($n = 17$ negative versus 15 neutral and 14 positive).

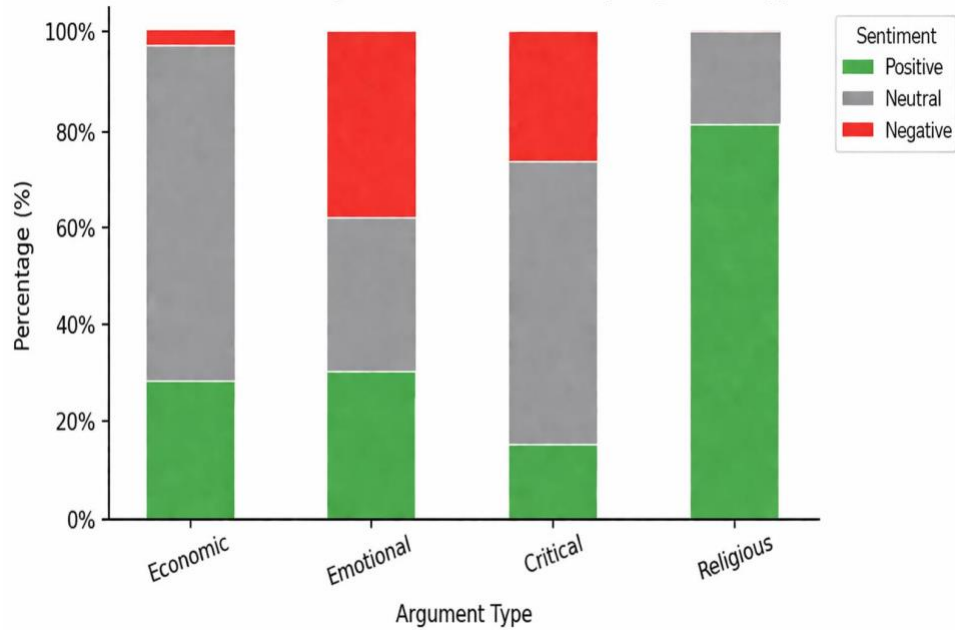


Figure 3. Sentiment composition within each argument frame (percentages within frame).

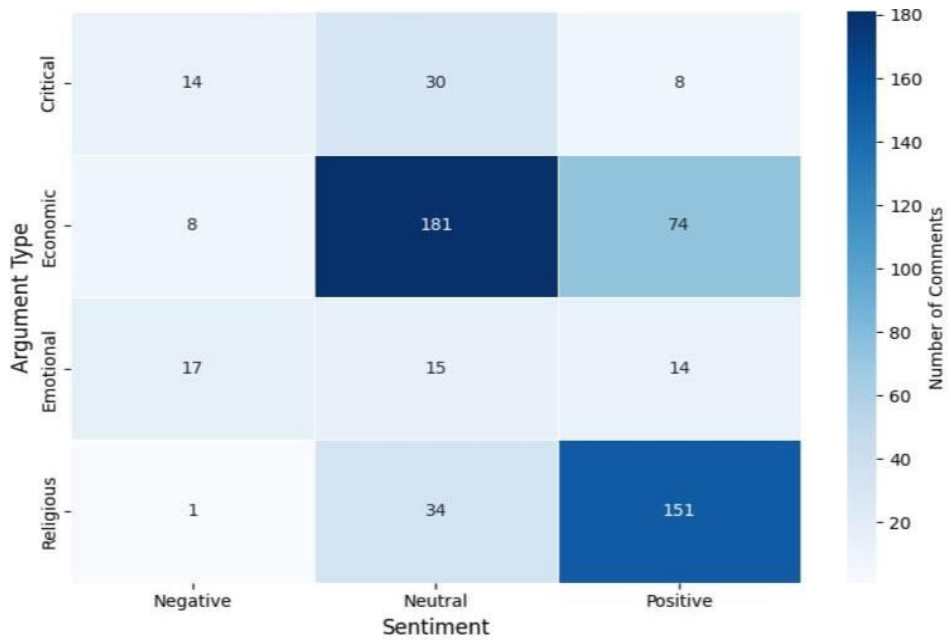


Figure 4. Frequency contingency table of argument frame and sentiment (cell values are counts).

Standardized residuals, shown in Figure 5, identify where the deviations from chance are concentrated. Religious frame combined with positive sentiment produced a residual of +7.31, the strongest positive deviation in the table, indicating that religious-frame comments are far more positive than random allocation would predict. The religious-frame and neutral-sentiment cell produced a residual of -5.79, the strongest negative deviation: a religious frame is the cell in

which neutrality is least likely to appear. Emotional frame and negative sentiment yielded +7.43, confirming that emotional framings cluster on the critical pole. Economic-frame and neutral-sentiment yielded +5.01, while economic-frame and positive-sentiment yielded −4.11, indicating that economic framings systematically suppress positive expression in favor of neutrality.

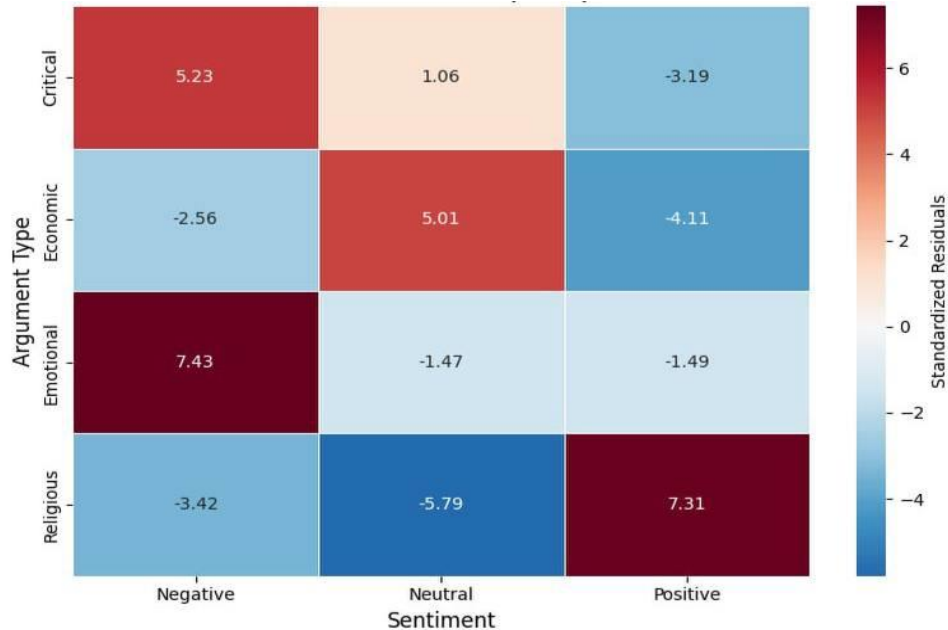


Figure 5. Standardized residuals of the argument frame $\times$ sentiment contingency table ($|residual| > 1.96$ is significant at $p < .05$).

A complementary Kruskal–Wallis test on emotional intensity across sentiment groups returned $H(2) = 109.39$, $p < .001$, indicating that emotional intensity differs significantly across sentiment categories. Spearman’s rank-order correlation between emotional intensity and sentiment polarity was $\rho = 0.198$, $p < .001$, a small positive association: higher intensity is loosely associated with sentiment that departs from neutral, but the relationship is not strong enough to treat intensity as a proxy for sentiment.

Table 2. Summary of inferential test results.

Test	Statistic	df	p-value	Effect size/interpretation
Chi-square (argument $\times$ sentiment)	$\chi^2 = 245.46$	6	$< .001$	Cramér’s $V = 0.474$ (medium–large)
Kruskal–Wallis (intensity by sentiment)	$H = 109.39$	2	$< .001$	Significant group differences in emotional intensity

Test	Statistic	df	p-value	Effect size/interpretation
Spearman (intensity × sentiment)	$\rho = 0.198$	—	$< .001$	Small positive monotonic association
Mann–Whitney U (sentiment by platform)	$U = 35,847$	—	.312	No significant platform difference in sentiment rank
Chi-square (frame by platform)	$\chi^2 = 8.21$	3	.042	Cramér’s $V = 0.122$ (small)

Note. n.s. = not significant. All tests are two-tailed.

Cross-Platform Differences (RQ4)

Figure 6 reports the normalized sentiment distribution across TikTok and Instagram. The two platforms produced similar overall patterns, with neutral being the modal category on both. Differences were small but directionally consistent: Instagram had a marginally higher share of negative sentiment (8.7% versus 6.3% on TikTok) and a marginally lower share of neutral (46.3% versus 48.1%). A Mann–Whitney U test confirmed that the rank ordering of sentiment did not differ significantly between platforms ($U = 35,847$, $p = .312$).

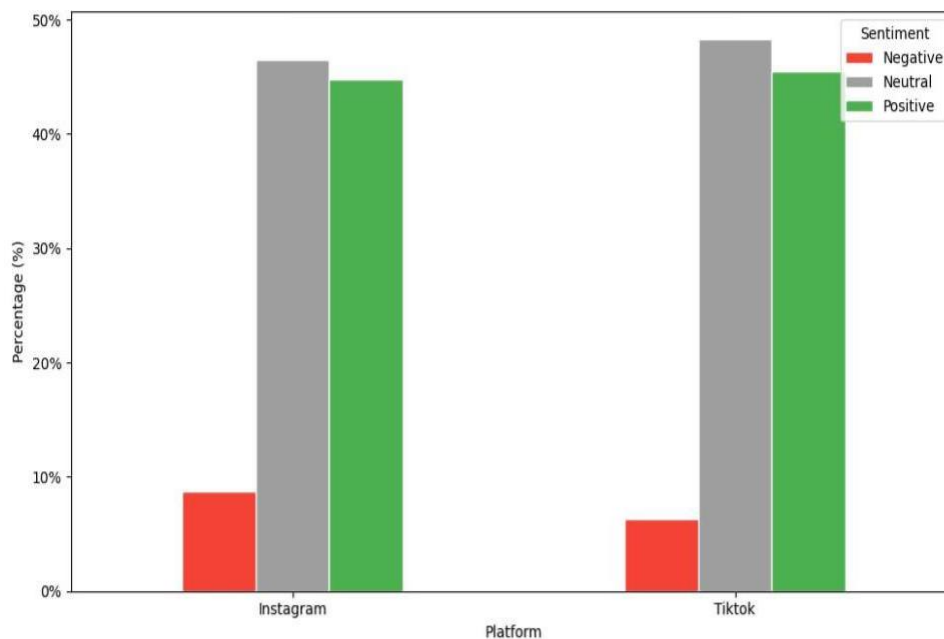


Figure 6. Sentiment distribution by platform (normalized within platform).

Argument-frame distribution, however, did differ. As Figure 7 shows, TikTok produced more comments in every argument category, but the religious frame was disproportionately represented on TikTok ($n = 116$, 36.5% of TikTok comments) compared with Instagram ($n = 70$,

30.6%). The chi-square test of independence on argument frame across platforms returned $\chi^2 = 8.21$, $df = 3$, $p = .042$, indicating that frame composition differs significantly between the two platforms. However, the effect size (Cramér's $V = 0.122$) was small.

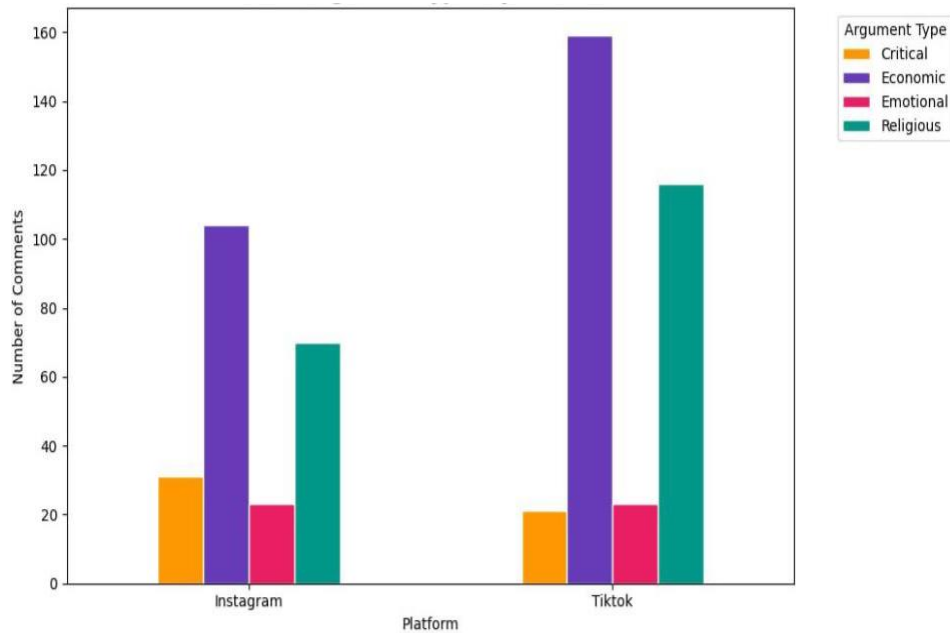


Figure 7. Argument-type frequency by platform.

The platform difference, therefore, qualifies H3. TikTok did produce higher volume, consistent with the platform's short-form, high-velocity affordance, but the prediction that religious framing would be more prominent on Instagram was not supported. Religious framing was, in fact, slightly more prevalent on TikTok in absolute and proportional terms, suggesting that short-form video has become a primary site of religious commentary in Indonesia, contrary to the expectation that reflective discourse migrates to longer-form platforms.

Predictors of Positive Sentiment (RQ5)

A binary logistic regression model estimated the effects of argument frame, emotional intensity, and misinformation on the probability that a comment expresses positive sentiment. The model returned a Nagelkerke pseudo- R^2 of 0.243 and a non-significant Hosmer–Lemeshow statistic ($\chi^2 = 7.12$, $p = .524$), indicating adequate fit.

Argument frame was a significant predictor of positive sentiment ($\beta = -1.188$, $SE = 0.146$, $Wald = 66.27$, $p < .001$, $OR = 0.305$). The negative sign, given the alphabetical coding of frames, indicates that movement from religious toward economic, critical, or emotional framing reduced the odds of positive sentiment by approximately 69.5%. Emotional intensity was also significant, though to a lesser extent ($\beta = -0.420$, $SE = 0.208$, $Wald = 4.07$, $p = .044$, $OR = 0.657$): higher emotional intensity reduced the odds of positive sentiment by approximately 34.3%.

Misinformation was not a significant predictor ($\beta = 0.580$, $SE = 0.578$, $Wald = 1.01$, $p = .315$), supporting H4: in this corpus, misinformation has no detectable effect on sentiment formation, despite a small positive coefficient. The regression results are summarised in Table 3.

Table 3. Binary logistic regression predicting positive sentiment.

Predictor	β	SE	Wald χ^2	p-value	OR
Argument frame	-1.188	0.146	66.27	< .001 ***	0.305
Emotional intensity	-0.420	0.208	4.07	.044 *	0.657
Misinformation	0.580	0.578	1.01	.315 n.s.	1.786
Constant	1.842	0.412	19.99	< .001 ***	—

Note. Outcome variable: positive sentiment (1) versus non-positive (0). $N = 547$. Nagelkerke pseudo- $R^2 = 0.243$. Hosmer–Lemeshow $\chi^2 = 7.12$, $p = .524$. * $p < .05$; *** $p < .001$; n.s. = not significant.

The correlation heatmap in Figure 8 contextualizes these results. Sentiment was moderately associated with argument frame ($r = 0.41$) and weakly with emotional intensity ($r = 0.20$). Argument frame and emotional intensity were more strongly correlated with each other ($r = 0.51$), suggesting that some argument frames carry their own emotional load (notably the emotional frame, by construction, and the critical frame in practice). Misinformation was effectively decoupled from every other variable ($|r| < 0.05$). A negative correlation between sentiment and likes ($r = -0.24$) hints that negatively framed comments attract higher engagement, a pattern consistent with prior research on the asymmetric virality of negative content (Vosoughi et al., 2018).

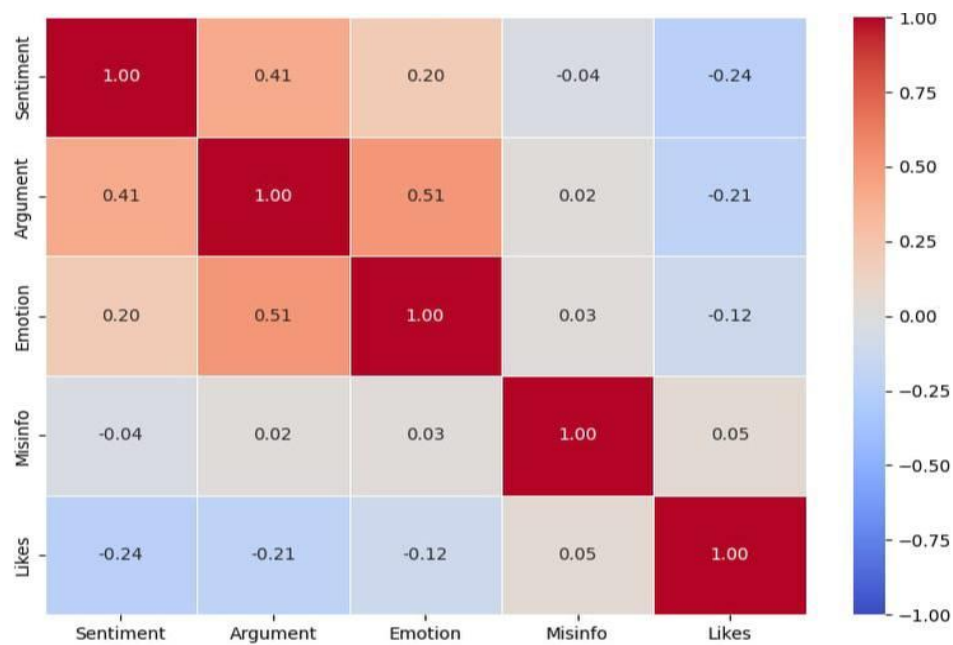


Figure 8. Correlation matrix of sentiment, argument frame, emotional intensity, misinformation, and likes.

Figure 9 displays mean emotional intensity by sentiment. Negative comments averaged 2.42 on the three-point scale, almost double the positive average of 1.21 and well above the neutral average of 1.43. The neutral category was not flat at the floor of the scale: neutral comments retained a measurable emotional charge, but one not directed toward an evaluative pole.

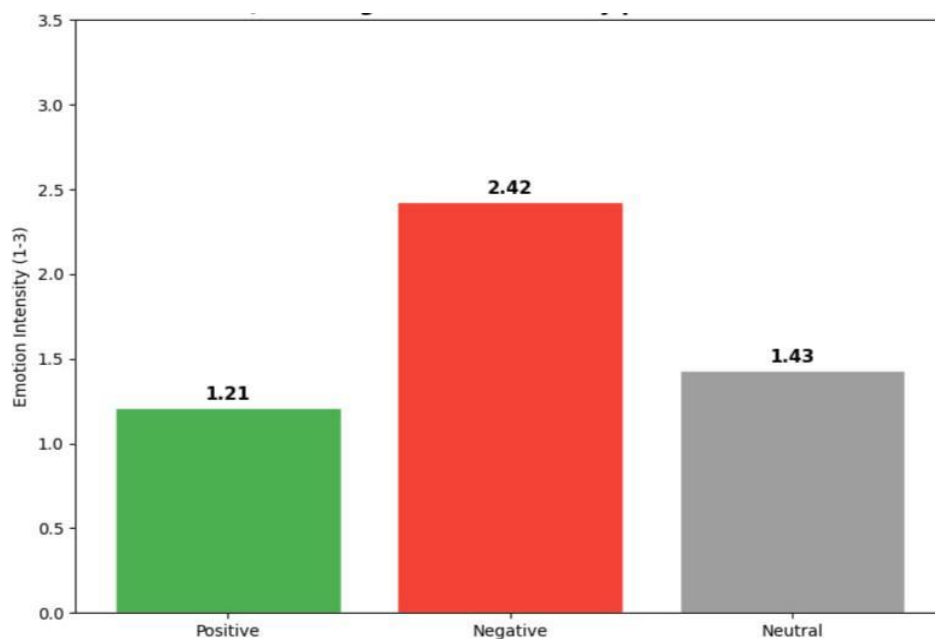


Figure 9. Mean emotional intensity by sentiment category (scale 1–3).

Figure 10 reports the distribution of misinformation across sentiment categories. Misinformation was present in a small minority of comments across all sentiment categories, but, counterintuitively, was slightly more prevalent in positive and neutral comments than in negative ones (2.0% in negative, 2.3% in neutral, 4.5% in positive). The pattern is consistent with the literature on benign misinformation (Lewandowsky et al., 2017): inaccurate claims that align with prevailing opinion attract less corrective attention than inaccurate claims that contradict it.

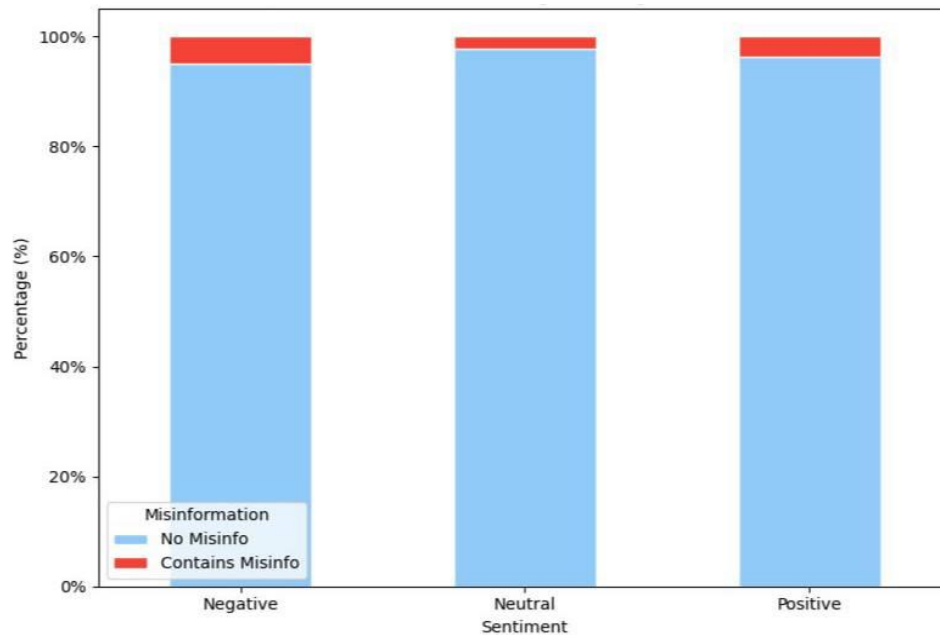


Figure 10. Misinformation proportion by sentiment category.

DISCUSSION

Pragmatic Framing Organizes a Religiously Contested Topic

The most consequential finding of the study is the relative weight of economic and religious framing in everyday discourse about a religiously contested financial product. Economic arguments outnumber religious arguments by 48.08% to 34.00%. In a Muslim-majority population responding to a topic that classical jurisprudence has treated as a hard prohibition, the pragmatic register is the default register, not the doctrinal one.

This finding is consistent with the behavioral economics literature on mental accounting (Thaler, 2016) and the framing of intertemporal decisions (Tversky & Kahneman, 1981), but it adds a religious-cultural specification. The Indonesian Muslim public does not appear unaware of the prohibition on *ribā*; the religious frame is the second-most-frequent category and is invoked with high consistency when it does appear. The pattern looks less like religious ignorance and more like frame partitioning: respondents activate the religious frame when the

conversation explicitly invites it (a creator post that foregrounds ḥalāl/ḥarām language) and the economic frame when the conversation is conducted in the register of routine consumption.

This connects with Slama's (2018) account of online piety among Indonesian Muslims as situational rather than continuous, and with Hjarvard's (2008) thesis on the mediatization of religion: religious authority is not absent from the digital public sphere but is invoked under specific discursive conditions. Where the conversation is framed in the language of fintech convenience, the religious frame recedes; it does not disappear.

The Religious Frame as Sentiment Anchor

The chi-square test and the standardized residuals reveal a structural asymmetry. Religious framing is the strongest sentiment anchor in the corpus: a religious-frame comment is overwhelmingly positive (residual = +7.31), rarely neutral (residual = -5.79), and rarely negative ($n = 1$ in the cell). Religious framing in this corpus is therefore not a vehicle for criticizing BNPL; it is a vehicle for affirming an Islamic normative position, even when that position is critical of the product. The positive sentiment, in other words, is positivity toward the religious value being defended, not toward BNPL.

This finding qualifies the standard sentiment-analysis assumption that sentiment polarity is a property of the comment's stance toward the explicit object of discussion. In religiously charged discourse, polarity may instead track the user's stance toward the normative frame they have chosen to deploy. A comment that says "ribā jelas haram, jangan ditawar-tawar" ("ribā is clearly forbidden, this is not negotiable") registers as positive sentiment toward the prohibition, even though it expresses negative judgment of the product. Future sentiment work in religious-discourse settings should therefore disentangle stance-toward-frame from stance-toward-object, perhaps through aspect-based sentiment analysis (Liu, 2012) or stance detection (ALDayel & Magdy, 2021).

The economic frame, by contrast, suppresses positive expression in favor of neutrality (residual for economic-neutral = +5.01; for economic-positive = -4.11). The economic-frame comment is the discursive workhorse: it describes interest rates, installment structures, and consumption needs in informational terms, without committing to a normative position. This is the language of consumer reasoning, and its modal polarity is neutral by construction.

Platform Affordances Shape Volume, Not Frame Composition (as Expected)

H3 predicted that Instagram, with its longer caption affordance and visual-first design, would host a higher proportion of religious and reflective commentary, while TikTok would host more spontaneous economic talk. The data partially contradicts this. TikTok produced both higher volume and a higher proportional share of religious framing (36.5% versus 30.6% on Instagram). The platform difference test was significant at conventional thresholds ($\chi^2 = 8.21$, $p = .042$), but the effect was small (Cramér's $V = 0.122$).

Two interpretations are plausible. The first is platform-historical: Indonesian Islamic content creators have migrated heavily to TikTok since 2022, building large religious-content audiences whose comment culture is religiously inflected. Hew (2024) documents this migration in his ethnography of Indonesian “dakwah TikTokers,” whose short-form videos on financial fiqh routinely attract six-figure numbers of comments. The second is platform-architectural: TikTok’s For You Page algorithm tends to amplify content with strong moral framing, because such content drives the engagement metrics the algorithm optimizes (Vijay & Gekker, 2021). The religious frame, with its high evaluative load, is exactly the kind of frame the algorithm rewards.

The finding revises the working assumption in the digital-religion literature that longer-form platforms produce more religious commentary. In the Indonesian case, the short-form platform has become the larger religious comment space, both in absolute and proportional terms.

Misinformation as a Decoupled Variable

Misinformation in this corpus is low in prevalence (3.11%) and statistically decoupled from sentiment (logistic-regression $p = .315$; correlation with sentiment $r = -0.04$). The result diverges from the broader misinformation literature, which has emphasized the role of inaccurate content in polarising opinion (Vosoughi et al., 2018; Pennycook & Rand, 2019). Two factors plausibly explain the divergence. First, the discursive domain may be unusually robust to misinformation. The ribā prohibition is widely known, the BNPL mechanism is straightforward to describe, and the inaccuracies that do appear (misquoted verses, exaggerated interest rates) tend to confirm prior beliefs rather than disrupt them. This is the dynamic Lewandowsky et al. (2017) characterize as benign misinformation: low-stakes inaccuracy that coexists with broadly accurate inference.

Second, the higher prevalence of misinformation in positive and neutral comments than in negative ones (4.5% versus 2.0%) suggests an asymmetric correction effect. Critical or negative commenters are subjected to scrutiny that often catches factual errors; supportive or neutral commenters draw less interrogation. The result is that misinformation flows more freely along the path of least resistance. However, in this domain, that path does not appear to shift sentiment formation in any detectable way. This finding should be read narrowly. It does not generalize to other religiously contested financial topics (cryptocurrency, multilevel marketing, investment scams), where misinformation has been documented as more consequential (Wahyudi & Sari, 2024). What it shows is that the BNPL–ribā discourse, despite touching on a topic many users feel strongly about, is not currently a domain where misinformation is doing visible discursive work.

Theoretical Implications

The study contributes to three literatures. For Islamic marketing and behavioral Islamic finance, it offers evidence that consumer reasoning about ribā in the digital marketplace is not organized around the prohibition itself but around the economic register in which the transaction is conducted. This is consistent with Mokhlis (2009) and Souiden and Rani (2015) on the situational character of religious self-identification in consumption, and extends their argument to user-generated discourse rather than survey self-report.

In framing theory, the finding is that frame choice strongly predicts sentiment. At the same time, emotional intensity adds only a small incremental predictive value, and misinformation adds none, supporting Entman's (1993) claim that the frame is the primary driver of evaluative response. The negative correlation between sentiment and likes ($r = -0.24$) further suggests that platform engagement metrics reward the negative pole, a finding consistent with Vosoughi et al. (2018) on social-media information diffusion.

For digital religion and the mediatization of religion (Hjarvard, 2008; Campbell, 2017), the study shows that religious authority is being negotiated on short-form video platforms that the digital-religion literature has historically under-studied. The migration of religious commentary to TikTok in Indonesia, and the strong sentiment-anchoring effect of the religious frame, suggest that mediatization in Muslim-majority contexts is taking algorithmic forms that the existing theoretical frameworks have not fully accommodated.

Practical Implications

Two practical implications follow. For sharia financial-literacy programs, the dominance of the economic frame implies that prohibitionist messaging, which begins with the ḥalāl/ḥarām binary, will reach only the audience already disposed to engage in religious terms. Reaching the larger economic-frame audience requires meeting that audience in its own register: financial cost analysis, total cost of ownership calculations, and explicit comparisons with sharia-compliant alternatives. The Indonesian Financial Services Authority's 2023 sharia financial-literacy index of 9.14% (Otoritas Jasa Keuangan, 2023), well below the conventional financial-literacy index, suggests substantial room for such reframed interventions.

For Islamic content creators, the platform asymmetry suggests that TikTok is the high-leverage channel for religious-frame messaging on financial topics, both because the platform attracts higher volume and because the religious frame on TikTok converts to positive sentiment at higher rates than the economic frame on either platform. Instagram remains useful for longer-form reflective content, but is no longer the primary site of religious commentary on consumer-finance topics.

CONCLUSION

This study set out to examine how Indonesian Muslim publics frame Buy-Now-Pay-Later services in their everyday social media talk, focusing on the interplay among sentiment, argument frame, emotional intensity, and misinformation in a corpus of 547 TikTok and Instagram comments collected between November 2022 and September 2025. Four findings stand out. First, the discourse is moderate, with neutral and positive sentiment together accounting for more than 92% of comments, and explicit negative judgment remaining a minority position. Second, economic framing dominates the conversation, outweighing religious framing by approximately 1.41 to 1, even though the topic itself is religiously contested. Third, the relationship between argument frame and sentiment is structural and strong ($\chi^2 = 245.46$, $p < .001$, Cramér's $V = 0.474$): religious framing functions as a positive-sentiment anchor for the normative position it defends. In contrast, economic framing systematically routes comments into neutrality. Fourth, in this domain, misinformation is present but inert: it does not significantly shape sentiment, behaving instead as benign noise that coexists with broadly accurate inference.

The conjunction of these findings supports a single overall claim: Indonesian Muslim digital discourse on *ribā* and BNPL is organized by economic pragmatism rather than religious normativity, even though religious normativity remains available and is invoked under specific discursive conditions. The implication for Sharia financial literacy is that the prohibitionist frame, on its own, will not reach the audience it most needs to reach, because that audience is already conducting the conversation in a different register. The implication for digital-religion research is that the short-form video platform has become a primary site of religious commentary in Muslim-majority Asia, a development that the existing theoretical frameworks have not yet fully integrated.

The study has six limitations that bound the interpretation of its findings. First, the corpus is drawn from four creators on two platforms. Although the comments capture a meaningful slice of Indonesian Muslim discourse on BNPL, they do not represent the entire universe of social media talk on the topic, and the findings should not be generalized to X (Twitter), YouTube, or messaging applications without further data.

Second, the corpus size of 547 comments, while adequate for the inferential tests reported, is small relative to the volume of platform-wide discussion. Statistical power for the misinformation analysis was particularly limited by the low base rate ($n = 17$), and a larger corpus would be needed to test cross-platform differences in misinformation with confidence.

Third, the coding scheme treats argument frames as mutually exclusive categories, which simplifies the analysis but underrepresents the small but non-negligible share of comments that combine frames (an economic–religious argument, for example, that calculates the cost of *ribā* in both monetary and spiritual terms). Future studies could adopt a multi-label coding scheme, with appropriate adjustments to the inter-coder reliability calculation.

Fourth, the study analyses comments at a single time point rather than across the lifecycle of a post. The dynamics of discourse, how sentiment shifts as a thread develops, are not captured here. A longitudinal extension could trace whether the religious frame is activated earlier or later in the comment lifecycle, and whether platform algorithms amplify particular frames over time. Fifth, the study does not collect user-level covariates (age, education, geographic location, prior religiosity), because these are not reliably available from public comment metadata. Survey or interview methods would be needed to test whether the discursive patterns identified here covary with user attributes, and to triangulate the framing analysis against self-reported religiosity.

Sixth, the inferential tests document association, not causation. The strong association between religious framing and positive sentiment is consistent with multiple causal mechanisms: religious framing may evoke positive evaluation, or users with positive views of the religious prohibition may select into the religious frame. Experimental or quasi-experimental designs, including frame manipulations or natural-experiment comparisons across creators with different framing styles, would be needed to identify the direction of effect.

These limitations suggest a research agenda. Cross-platform extension to X and YouTube, multi-label frame coding, longitudinal lifecycle analysis, integration with user-level survey data, and experimental frame manipulation each open useful next steps. A particularly promising direction is integrating large-language-model-based stance detection with the manual frame coding used here, thereby allowing the analytical pipeline to scale while preserving the conceptual precision that hand-coding offers.

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