

Sentiment And Repurchase Signals In Indonesian Fresh-Produce E-Commerce Reviews: A Pilot Text-Mining Study

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ABSTRACT: Online fresh-produce retailing presents distinctive quality and delivery uncertainties that influence consumer evaluations and repurchase intentions. This study contributes a leakage-controlled, polarity-aware text-mining framework for examining consumer sentiment and repurchase signals in unsolicited online reviews. Using 113 public Tokopedia reviews covering 31 fresh-produce products, this pilot study employed lexicon-based sentiment classification and logistic regression with product-clustered standard errors. The findings reveal predominantly positive consumer sentiment, although explicit repurchase intentions appear less frequently. Consumer sentiment demonstrates a significant positive association with repurchase signals, while product-quality mentions show no significant relationship. Unexpectedly, positive delivery mentions exhibit a negative association with repurchase signals, potentially reflecting review-length constraints rather than unfavorable delivery experiences. These findings extend the methodological application of consumer-generated content analysis by demonstrating the feasibility of extracting distinct behavioral signals while addressing classification bias. Online retailers can leverage this framework to monitor consumer experiences and identify opportunities for service improvement.

Keywords: Sentiment Analysis; Text Mining; Repurchase Intention; Fresh Produce; E-Commerce; Pilot Study

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INTRODUCTION

E-commerce for fresh produce categories such as vegetables, fruits, and fresh food has grown rapidly in Indonesia, yet it differs fundamentally from non-perishable categories because consumers cannot physically inspect product quality before purchase. Prior research indicates that e-logistics service quality (E-LSQ) plays a critical role in bridging the gap between the product quality displayed on the application and the quality consumers actually receive, making it an important determinant of satisfaction and continuance intention toward fresh produce e-commerce services (Monoarfa et al., 2024).

Other studies in the Indonesian context find that perceived ease of use, perceived usefulness, and customer satisfaction are key drivers of repurchase intention in online shopping (Nuralam et al., 2024), consistent with broader evidence that ease of use, perceived value, and service quality shape customer experience and behavioral outcomes across Indonesian digital commerce and financial technology platforms (Elliyana et al., 2022a; Elliyana et al., 2022b), while studies on fresh produce e-commerce specifically emphasize the role of logistics service quality in shaping consumers' continuance intention (Monoarfa et al., 2024). Meanwhile, research on repurchase intention for general shopping products in Indonesian e-commerce underscores the mediating role of e-satisfaction between trust, service innovation, ease of use, and repurchase intention (Pangestu & Setiyaningrum, 2023).

Survey-based studies of this kind capture how consumers recall and rate their experience after the fact, filtered through the constructs a questionnaire happens to ask about; they are less able to surface the specific, spontaneously mentioned complaints or praise (e.g., a torn plastic bag, unexpectedly ripe mangoes) that consumers volunteer unprompted. Text mining of unsolicited reviews captures a different and complementary slice of consumer experience: naturally occurring language, produced without a survey instrument's framing, now of post-purchase evaluation. This distinction motivates the present study's design and defines the specific gap it addresses.

Methodologically, most Indonesian studies on repurchase intention including those on fresh produce still rely on primary survey data analyzed with Structural Equation Modeling (SEM/PLS-SEM). This approach is valid but is typically limited to a relatively small number of respondents and is prone to self-report bias. Text mining and sentiment analysis of online consumer reviews have been widely used internationally to uncover determinants of satisfaction and repurchase intention in a more ecologically valid way, since they are drawn from voluntarily expressed consumer opinions at scale (Kumar et al., 2023; G. Wang, 2025). However, no published study has yet applied text mining specifically to Indonesian-language fresh-produce e-commerce reviews to examine how sentiment and aspect-level mentions relate to repurchase signals; this remains an underexplored gap that the present pilot begins to address. This study therefore aims to: (1) classify consumer sentiment toward the fresh produce online shopping experience based on public reviews; and (2) explore how review sentiment, product-quality mentions, and delivery-service mentions relate to repurchase-intention signals through a text-mining and statistical modeling approach. Its contribution is methodological and empirical rather than purely applicative: it demonstrates and pilot-validates a leakage-free, polarity-aware Indonesian-language review-mining pipeline for this understudied product category, with cluster-robust inference to account for reviews nested within products.

THEORETICAL REVIEW

Expectation-Confirmation Theory, Technology Acceptance, and E-Logistics Service Quality (E-LSQ)

Repurchase intention refers to a consumer's tendency to make a repeated purchase from the same platform or product category in the future, and is a key indicator of e-commerce business sustainability. In the context of fresh produce, research integrating the expectation-confirmation theory of technology acceptance model (EC-TAM), product evaluation models, and E-LSQ shows that confirmation of logistics service quality is a substantial determinant of perceived product quality, satisfaction, and continuance intention toward fresh produce e-commerce services (Monoarfa et al., 2024). Freshness, information accuracy, and delivery timeliness receive

particular attention given the perishable nature of the product. Across this literature, perishability changes logistics priorities: freshness preservation, accurate flow of condition and tracking information, and fast delivery are treated as service-critical rather than merely operational preferences (Pal & Kant, 2019, 2020; X. Wang et al., 2017). The reason is consistent across supply-chain, routing, and e-commerce studies: perishable goods deteriorate with time, temperature abuse, and handling, so delays or poor information directly raise spoilage, dissatisfaction, and waste (Li et al., 2021; Liu & Hou, 2023; Tsang et al., 2020).

These three frameworks are invoked here for distinct and complementary reasons rather than as an undifferentiated bundle. Expectation-confirmation theory supplies the general logic of post-purchase evaluation used to interpret why a review's overall sentiment might relate to a repurchase signal. E-LSQ supplies the specific service dimensions delivery timeliness, packaging, handling through which that confirmation or disconfirmation is most likely to be triggered for a perishable category. The technology-acceptance element (TAM) is the least central of the three for this study: because the analysis does not measure perceived usefulness, ease of use, or platform-adoption variables, TAM is retained only as background context on why consumers adopt fresh-produce e-commerce at all, not as a framework being tested here. Review sentiment as an aggregate expression of the confirmation or disconfirmation of consumer expectations is expected to relate to the likelihood that a review contains an explicit indication of repurchase intention.

H1: The review sentiment (positive/negative/neutral; sentiment score) associated with the likelihood that a review contains an explicit repurchase-intention signal.

Product Quality Confirmation and Repurchase Intention

Several studies in Indonesian e-commerce consistently find that customer/e-satisfaction mediates the influence of trust, ease of use, and service innovation on repurchase intention, although the direct effect of these factors is not always significant (Nuralam et al., 2024; Pangestu & Setiyaningrum, 2023). Freshness and product-quality confirmation are frequently cited as central concerns for perishable-category consumers, since quality cannot be verified prior to delivery.

H2: An explicit positive or negative mention of product-quality/freshness attributes in a review relate to the likelihood of a repurchase-intention signal.

E-Logistics Service Quality and Delivery Experience

Delivery timeliness, packaging quality, and courier handling are core dimensions of E-LSQ that shape consumers' post-purchase evaluation of fresh produce e-commerce, particularly because product deterioration risk increases with delivery delay (Gulc, 2021; Monoarfa et al., 2024; Wu et al., 2024). Reviews that explicitly reference delivery experience may therefore carry additional signal value for repurchase-intention indication. Based on the theoretical review above, this study proposes a conceptual framework as illustrated in Figure 1. The framework is exploratory; hence, it organizes associations to be described, not effects to be confirmed.

H3: An explicit positive or negative mention of delivery-service attributes in a review relate to the likelihood of a repurchase-intention signal.

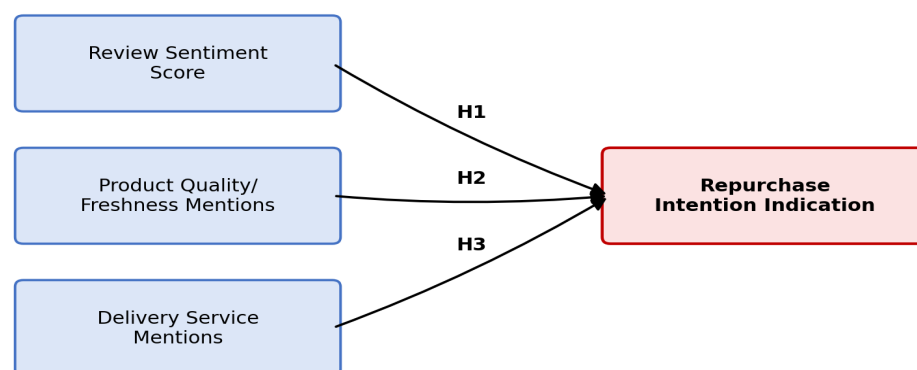


Figure 1. Conceptual Framework of the Study

RESEARCH METHOD

This study uses a non-experimental quantitative design combining text mining and statistical analysis of secondary data consisting of consumer reviews publicly published on an e-commerce platform. This approach was chosen to capture consumer sentiment and behavior in a more ecologically valid way than self-reported survey data. The unit of analysis is the review text, not individual respondents; consequently, this study does not report respondent demographic characteristics, as no survey participants were recruited and no personally identifiable reviewer information was collected.

The population is public consumer reviews for fresh produce categories on Indonesian e-commerce platforms. Reviews were collected from Tokopedia on 4–6 July 2026. At this pilot stage, a sample was drawn purposively from publicly indexed review pages, covering three subcategories: vegetables (13 products), fruits (10 products), and fresh fish/meat (8 products), totaling 31 products and 113 textual reviews. Inclusion criteria were: (a) Indonesian-language reviews, (b) substantive text content (not merely a star rating), and (c) the product explicitly described as a fresh (perishable) item.

Reviewer account names displayed on reviews are information already published openly by the platform; for reporting purposes, reviewer identities are not disclosed and only aggregated review text is analyzed. This pilot dataset ($N=113$) is intended to demonstrate the feasibility of the text-mining pipeline and is not intended as a population-representative sample; the interpretation of results in the Results section is therefore exploratory and indicative.

Because the 113 reviews are nested within 31 products (2 to 7 reviews per product; $M = 3.6$), reviews of the same product likely share seller quality, packaging, and logistics arrangements, so an assumption of independent observations is doubtful. All models reported below therefore use product-clustered standard errors rather than ordinary Wald standard errors (see Data Analysis below).

The text-mining pipeline comprised: (1) text pre-processing (case folding and tokenization); (2) sentiment classification using a manually constructed Indonesian/English-language lexicon of positive and negative words attested in this review corpus, producing a net sentiment score (positive word count minus negative word count) and a positive/neutral/negative label; (3) polarity-coded attribute tagging for product quality/freshness and delivery service (each coded as a positive-mention dummy and a negative-mention dummy, rather than a single presence/absence dummy); and (4) binary labeling of repurchase-intention signal based on explicit phrases ('langganan'/repeat customer, 'recommended'/'recommend'/'rekomended', 'selalu'/always, 'next order', 'sudah berkali kali beli'/repeated purchase phrasing). To prevent label leakage, all words used to detect the repurchase-intention signal were explicitly excluded from the sentiment lexicon, so no term can simultaneously define the outcome and contribute to the sentiment-score predictor. The full keyword lists used for sentiment, aspect polarity, and repurchase-signal detection, and the resulting review-level codes, are available from the authors and will be added to the Zenodo deposit alongside this revision.

Data analysis was performed in Python 3.12 (pandas 2.x, NumPy 2.4.4, SciPy 1.17.1, scikit-learn 1.8.0) using unpenalized (maximum-likelihood) logistic regression scikit-learn's LogisticRegression fit with no regularization ($C = \infty$), the lbfgs solver, and a convergence tolerance of $1e-10$ to examine RQ1–RQ3 with repurchase-intention signal as the dependent variable. Because scikit-learn's default L2-regularized fit is not compatible with classical Wald inference, regularization was explicitly disabled for all reported models. Standard errors were computed as cluster-robust (sandwich) standard errors, clustered by product, with the small-sample correction factor $G/(G-1) \times (N-1)/(N-K)$ commonly applied to cluster-robust estimators (Cameron & Miller, 2015), where $G = 31$ product clusters, $N = 113$ reviews, and K is the number of estimated parameters. With 31 clusters, cluster-robust inference is workable but modest by conventional guidance (which favors 30–50+ clusters), and should be treated as indicative rather than asymptotically precise at this pilot sample size.

RESULTS

Descriptive Overview and Sentiment Classification

The pilot dataset consists of 113 reviews from 31 products across three fresh produce subcategories on Tokopedia. The distribution of reviews by subcategory is presented in Table 1.

Table 1. Distribution of Reviews by Fresh Produce Subcategory (N=113)

Subcategory	Number of Products	Number of Reviews	Percentage
Vegetables	13	42	37.2%
Fruits	10	34	30.1%
Fresh Fish/Meat	8	37	32.7%
Total	31	113	100%

Lexicon-based sentiment classification, using the leakage-free lexicon described in Research Method, produced the distribution shown in Table 2. The majority of reviews (81.4%) are positively toned, consistent with the generally high star ratings (mostly 4–5) reported on the observed product pages.

Table 2. Distribution of Review Sentiment (leakage-free lexicon)

Sentiment Category	Number of Reviews	Percentage
Positive	92	81.4%
Neutral	12	10.6%
Negative	9	8.0%

At the attribute level, 71 of 113 reviews (62.8%) explicitly mention product quality/freshness 61 (54.0%) positively and 17 (15.0%) negatively, with a small overlap of reviews mentioning both while 48 of 113 reviews (42.5%) explicitly mention delivery service 45 (39.8%) positively and 5 (4.4%) negatively. A total of 33 of 113 reviews (29.2%) contain an explicit repurchase-intention signal (e.g., '*langganan*'/repeat customer, '*recommended*', '*selalu*'/always).

Table 2b. Polarity-Coded Attribute Mentions (N=113)

Aspect	Positive Mentions	Negative Mentions	Any Mention
Product Quality/Freshness	61 (54.0%)	17 (15.0%)	71 (62.8%)
Delivery Service	45 (39.8%)	5 (4.4%)	48 (42.5%)

Association Testing of Repurchase-Intention Signals

A logistic regression model was fitted with repurchase-intention signal (binary) as the outcome and sentiment score, product-quality mention (positive/negative), and delivery-service mention (positive/negative) as predictors, following Equation (1), used descriptively with product-clustered inference rather than as a confirmatory significance test.

$$\text{logit}(P) = \beta_0 + \beta_1(\text{SentimentScore}) + \beta_2(\text{QualityPositive}) + \beta_3(\text{QualityNegative}) + \beta_4(\text{DeliveryPositive}) + \beta_5(\text{DeliveryNegative}) \quad \dots\dots\dots (1)$$

Table 3 presents the estimation results, with product-clustered 95% confidence intervals. The model correctly classified 71.7% of reviews. Sentiment score (H1) is positively and significantly associated with the repurchase-intention signal ($B = 0.476$, cluster-robust $SE = 0.156$, $p = .002$; $OR = 1.61$, 95% $CI [1.19, 2.18]$): each one-point increase in net sentiment word count is associated with roughly 61% higher odds of an explicit repurchase-intention signal. Removing the shared vocabulary between the sentiment lexicon and the repurchase-signal definition therefore did not weaken this association if anything it clarified it, suggesting the link is not solely a leakage artefact.

Positive and negative product-quality mentions (H2) are both statistically indistinguishable from zero (positive: $B = -0.037$, $p = .927$; negative: $B = -0.632$, $p = .363$); once sentiment score is in the model, explicitly raising the quality/freshness attribute favorably or unfavorably carries no additional detectable association with the repurchase signal in this sample. Delivery mentions

(H3) show an asymmetric and unexpected pattern: a positive delivery mention is associated with significantly lower odds of an explicit repurchase-intention signal ($B = -1.306$, cluster-robust SE = 0.533, $p = .014$; OR = 0.27, 95% CI [0.10, 0.77]), while a negative delivery mention shows a positive but highly imprecise and non-significant coefficient based on only 5 cases ($B = 0.698$, $p = .545$, 95% CI [0.21, 19.24]). The negative association for positive delivery mentions runs counter to the expectation-confirmation/E-LSQ reasoning in the Theoretical Review and is interpreted with caution in the Discussion.

Table 3. Corrected Logistic Regression Results for Repurchase-Intention Signal (N=113, 31 product clusters, unpenalized MLE with cluster-robust SE)

Variable	B	Cluster SE	p-value	Odds Ratio	95% CI (OR)
Constant	-1.514	0.446	.001**	0.220	[0.092, 0.528]
Sentiment Score (H1)	0.476	0.156	.002**	1.609	[1.185, 2.184]
Quality-Positive (H2)	-0.037	0.405	.927	0.964	[0.435, 2.133]
Quality-Negative (H2)	-0.632	0.694	.363	0.532	[0.136, 2.073]
Delivery-Positive (H3)	-1.306	0.533	.014*	0.271	[0.095, 0.769]
Delivery-Negative (H3)	0.698	1.152	.545	2.010	[0.210, 19.237]

Note: * $p < .05$, ** $p < .01$. Standard errors and confidence intervals are cluster-robust (clustered by product, N=113, G=31), with the small-sample correction of Cameron & Miller (2015).

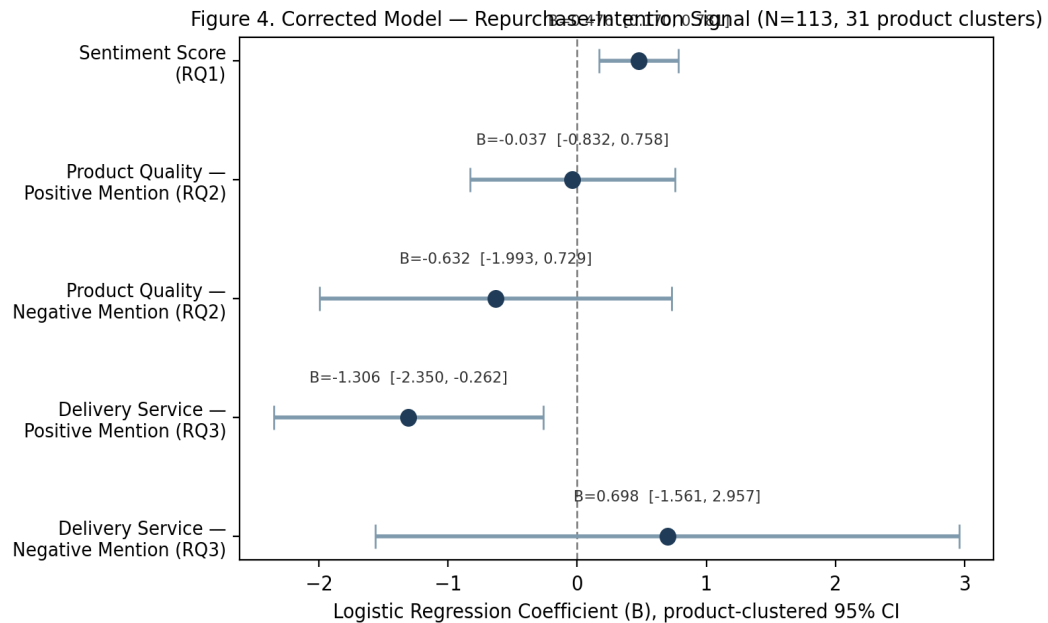


Figure 4. Corrected logistic regression coefficients for repurchase-intention signal (N=113), product-clustered 95% confidence intervals.

DISCUSSION

Discussion

The findings demonstrate that consumer-generated reviews provide meaningful insights into post-purchase evaluations and repurchase-intention signals in fresh-produce e-commerce. The predominance of positive sentiment aligns with Monoarfa et al. (2024), who emphasized the importance of electronic logistics service quality, product satisfaction, and continuance intention in fresh-produce purchasing. Nuralam et al. (2024) similarly identified customer satisfaction as an important determinant of repurchase intention in Indonesian e-commerce. However, the lower occurrence of explicit repurchase signals suggests that favorable evaluations do not necessarily translate into expressed purchasing commitments. This distinction extends conventional consumer-behavior perspectives by demonstrating that satisfaction-related expressions and loyalty language represent related but conceptually different dimensions of unsolicited consumer feedback. The findings therefore highlight the importance of distinguishing general evaluations from explicit behavioral intentions when interpreting online reviews.

The prominence of freshness-related mentions reflects the distinctive characteristics of perishable products, where perceived quality depends on product condition, storage, and fulfillment reliability. Liu and Hou (2023) emphasized the operational importance of cold-chain logistics in maintaining fresh-product quality, while Monoarfa et al. (2024) established the relevance of logistics service quality for continued fresh-produce purchasing. However, the present findings indicate that product-quality mentions, regardless of polarity, have no statistically detectable association with repurchase-intention signals after accounting for overall sentiment. This suggests that general evaluative language may capture information that individual quality mentions contribute to consumer assessments. Nevertheless, the absence of statistical significance does not establish that product quality lacks behavioral relevance. The limited sample and sparse aspect-specific observations may restrict the detection of independent relationships. The findings indicate that mentioning freshness does not necessarily communicate a willingness to repurchase.

The positive association between sentiment score and repurchase-intention signals represents the study's most consistent finding. This relationship supports the theoretical expectation that favorable post-purchase evaluations accompany consumers' intentions to continue purchasing, as suggested by Monoarfa et al. (2024) and Pangestu and Setiyaningrum (2023). Unlike conventional survey-based assessments, this study identifies the relationship through naturally occurring consumer expressions. Kumar et al. (2023) similarly demonstrated the analytical value of online reviews for identifying determinants of grocery application satisfaction. The present study extends this methodological perspective by showing that sentiment retains a positive association with explicit repurchase language after correcting lexical overlap between predictor and outcome classifications. However, sentiment should be interpreted as an observable proxy for post-purchase evaluation rather than a direct measurement of expectation confirmation. The findings establish an association between evaluative and loyalty-related language without demonstrating the psychological mechanisms underlying consumer repurchase decisions.

The negative association between positive delivery-service mentions and repurchase-intention signals presents an unexpected finding. Previous research generally associates satisfactory logistics performance with customer satisfaction and continued purchasing (Monoarfa et al., 2024; Wu et al., 2024). The apparent contradiction may reflect differences between consumers' actual behavioral intentions and their expressions in unsolicited reviews. Reviewers frequently provide brief evaluations, which may prioritize delivery speed, packaging, or product condition without explicitly expressing future purchasing intentions. Consequently, positive delivery comments may coexist less frequently with repurchase language because of limited textual space rather than unfavorable attitudes toward delivery services. This textual crowding-out explanation remains speculative and requires further examination. Review length, topic selection, and aspect co-occurrence should be considered before interpreting the relationship as a substantive behavioral phenomenon. Moreover, the negative-delivery category contains very few observations, making its estimated association too imprecise for reliable interpretation.

These findings also emphasize the methodological importance of distinguishing aspect presence from aspect polarity. Combining favorable and unfavorable mentions within a single indicator can obscure differences in consumer evaluations and produce misleading associations. Lakshmi et al. (2025) highlighted the importance of classification approaches in extracting meaningful sentiment from e-commerce reviews, while Kumar et al. (2023) demonstrated the value of identifying distinct satisfaction-related attributes through text mining. The present study advances this approach by integrating polarity-aware classification with corrections for label leakage between sentiment and repurchase indicators. Nevertheless, methodological refinement does not eliminate the limitations of a small exploratory dataset. Product-clustered standard errors account for within-product dependence, but the limited number of clusters and sparse textual categories may affect inferential reliability (Cameron & Miller, 2015). Accordingly, the reported associations should be considered preliminary rather than conclusive evidence of consumer behavior.

The study's principal contribution lies in clarifying the distinction between established consumer-behaviour constructs and their observable representations in unsolicited online reviews. Conventional electronic logistics service quality and expectation-confirmation

perspectives primarily examine perceived satisfaction and behavioral intention through structured measures. Review mining instead captures selective expressions of consumer experiences. The findings demonstrate that aggregate sentiment may offer more consistent information about explicit repurchase language than isolated product-quality or delivery mentions. However, theoretically important service attributes do not necessarily exhibit independent statistical relationships when operationalized through short-form text. This distinction identifies a measurement challenge in transferring survey-based theoretical relationships into consumer-review analytics. Future studies should employ larger, longitudinal, and multi-platform datasets, validate classification accuracy through human annotation, and examine review length and aspect co-occurrence. Linking review-derived signals with verified repeat purchases would further establish their predictive validity.

From a managerial perspective, the findings support integrating sentiment analysis into routine customer-feedback monitoring while avoiding the assumption that positive reviews necessarily indicate loyalty. Fresh-produce retailers should monitor overall sentiment alongside polarity-specific product-quality and delivery indicators to identify emerging service concerns. Managers should also distinguish favorable delivery evaluations from explicit repurchase commitments rather than treating them as interchangeable measures. Integrating review analytics with structured customer feedback and verified purchasing records would improve retention monitoring and reduce interpretive bias. Such practices can help online retailers prioritize freshness management, strengthen fulfilment quality, and develop more evidence-based customer retention strategies.

CONCLUSION AND FURTHER STUDY

This pilot study's central insight is that Indonesian-language fresh-produce reviews carry detectable, interpretable signal about product quality, delivery experience, and repurchase intent and that a lexicon-based text-mining pipeline, once corrected for label leakage and aspect-polarity conflation and estimated with product-clustered inference, can extract that signal at a scale and ecological validity that survey-based methods do not easily match. After these corrections, overall review sentiment is a statistically significant, positive correlate of an explicit repurchase-intention signal, while product-quality mentions show no independent association and positive delivery mentions show an unexpected negative association plausibly linked to the short-text format of these reviews rather than to delivery satisfaction itself. The pilot's contribution is to validate the feasibility of this corrected pipeline for an understudied product category and to surface through direct correction rather than mere caveat the specific measurement refinements (leakage-free sentiment computation, polarity-coded aspect tagging, cluster-robust estimation) that full-scale studies in this area will need.

This study is subject to important limitations. First, the pilot sample size ($N=113$) is small and drawn purposively from products surfaced in public search results, so it is not statistically representative of the population of Indonesian fresh-produce reviews and is prone to selection bias. Second, sentiment classification and aspect-polarity tagging rely on a manually constructed keyword lexicon that has not been cross-validated against human annotation or benchmarked against more advanced models such as IndoBERT; while repurchase-signal terms are now explicitly excluded from the sentiment lexicon to avoid label leakage, the lexicon itself is a reconstruction by the analysis team and may not perfectly match how a different coder would classify the same text. Third, individual review-level star ratings were not available, so a rating-based predictor could not be included. Fourth, data are drawn from a single platform (Tokopedia) collected over a three-day window (4–6 July 2026), which may not capture seasonal or promotional variation in review content. Fifth, although product-clustered standard errors now account for the nested structure of reviews within products, the number of clusters ($G=31$) is modest for the cluster-robust sandwich estimator's asymptotic properties, and the delivery-negative estimate in particular rests on only 5 observations and should not be over-interpreted.

Future research should: (1) substantially expand data volume (ideally several hundred to several thousand reviews per subcategory) through official API access or platform-compliant crawling, which would also increase the number of product clusters available for cluster-robust or multilevel estimation; (2) validate sentiment and aspect-polarity classification with human

annotation and/or a pretrained language model (e.g., IndoBERT); (3) test the review-length crowding-out explanation for the delivery finding directly, for example by including review length as a covariate or by studying longer-form reviews where quality, delivery, and loyalty language are less likely to compete for space; and (4) incorporate individual ratings and additional control variables (price, seller reputation, specific product category).

ETHICAL DISCLOSURE

This study relies exclusively on textual content from consumer reviews that are publicly displayed on an e-commerce platform; it did not involve direct interaction with human participants (e.g., surveys, interviews, or experiments).

CONFLICT OF INTERESTS

The authors declare no conflict of interest.

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