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Article

Cross-Sector Sentiment and Topic Analysis of Indonesian Digital Platform Applications: A Text Mining Study of Google Play Store Reviews

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Abstract: The rapid expansion of Indonesia's digital economy has produced a large, continuously generated body of user feedback on mobile application stores, yet most prior sentiment-analysis studies examine a single application or a single sector in isolation, leaving cross-sector comparison largely unexplored. This study applies text mining to 841,664 Google Play Store reviews collected from eight widely used Indonesian digital platform applications spanning five sectors: fintech e-wallets (DANA, OVO), e-commerce (Blibli, Bukalapak, Tokopedia), on-demand services (Gojek), education technology (Ruang Guru), and travel (Traveloka). A rating-derived sentiment label (negative, neutral, positive) was validated using a TF-IDF and Logistic Regression classifier, which achieved 85.8% accuracy and a macro F1-score of 0.858 on held-out data. Non-negative matrix factorization (NMF) topic modeling was applied to negative reviews within each sector to surface dominant pain-point themes, and a Kruskal-Wallis test compared rating distributions across sectors. Results show statistically significant differences in user satisfaction across sectors ($H = 160{,}561.5$, $p < .001$, $\varepsilon^2 = 0.191$), with the fintech e-wallet sector exhibiting markedly lower satisfaction (63.4% negative reviews, mean rating = 2.35) than education technology (9.6% negative, mean rating = 4.51). Topic modeling reveals that e-wallet dissatisfaction concentrates on balance/fund-safety trust concerns and identity-verification (KYC) upgrade friction, distinguishing it from complaints in other sectors that center on pricing and service delivery. The findings extend Technology Acceptance Model/UTAUT-based fintech adoption research with large-scale textual evidence and offer practical guidance for prioritizing fintech user-experience improvements around trust and verification processes.
Keywords: sentiment analysis; text mining; fintech; e-wallet; topic modeling; user satisfaction; Indonesia

1. Introduction

Indonesia's digital economy has expanded rapidly over the past decade, with financial technology (fintech), e-commerce, on-demand services, education technology, and online travel platforms becoming embedded in everyday consumer behavior. As of early 2022, the Financial Services Authority (Otoritas Jasa Keuangan, OJK) had registered 103 licensed fintech lending providers, and digital payment platforms such as e-wallets have become a primary channel through which Indonesian consumers transact [1]. This growth has been accompanied by a parallel expansion of publicly available user feedback: every major consumer application accumulates thousands of Google Play Store reviews that combine a quantitative star rating with unstructured free-text commentary, forming a large-scale, continuously updated "voice of customer" (VOC) dataset.

Prior research on Indonesian app-store sentiment has predominantly examined individual applications or single sectors   for example, sentiment analysis of peer-to-peer (P2P) lending applications [2], digital bank applications [3], government mobile applications [4], and a range of single-app case studies spanning skincare e-commerce, ride-hailing, and streaming services [5], [6]. While these studies establish that rating-derived or lexicon-derived sentiment labels are effective proxies for user opinion, comparative evidence across sectors fintech versus e-commerce versus on-demand services versus education technology versus travel remains scarce. This gap is consequential because it is unclear whether dissatisfaction patterns observed in fintech applications are sector-specific (e.g., driven by trust and security concerns unique to handling consumer funds) or simply reflect general dissatisfaction with mobile applications in Indonesia.

This study addresses that gap using a large, real-world corpus of 841,664 Google Play Store reviews of eight Indonesian digital platform applications, originally compiled by an independent Kaggle contributor via Play Store scraping for sentiment-analysis research [7]. The study poses three research questions: (RQ1) Does user satisfaction, measured through star ratings and rating-derived sentiment, differ significantly across digital platform sectors? (RQ2) What are the dominant complaint themes within each sector, as revealed through unsupervised topic modeling of negative reviews? (RQ3) Does the fintech e-wallet sector exhibit a distinct dissatisfaction profile relative to non-financial digital platforms, and if so, what does this imply for fintech trust and adoption theory?

The remainder of this article is organized as follows. The rest of Section 1 reviews related work on sentiment analysis of Indonesian mobile applications and fintech adoption theory. Section 2 (Materials and Methods) describes the dataset, preprocessing, sentiment-labeling validation, topic-modeling, and statistical procedures. Section 3 presents the Results. Section 4 (Discussion) interprets the findings in relation to prior literature and behavioral/adoption theory, and Section 5 concludes with contributions, limitations, and directions for future research.

1.1 Sentiment Analysis of Indonesian Mobile Application Reviews

Sentiment analysis of Google Play Store reviews has become a common method for evaluating Indonesian digital services. Amrie et al. [2] applied TF-IDF feature extraction with Naïve Bayes classification to compare sentiment across three P2P lending applications, finding substantial variation in positive-sentiment proportions (36%–77%) between platforms. Santoso et al. [3] compared Random Forest and Support Vector Machine classifiers on digital bank application reviews and found predominantly positive sentiment associated with usability and speed. Hamid et al. [4] combined sentiment analysis with topic modeling on Indonesian mobile government applications to identify service-quality themes, an approach methodologically related to the present study's use of topic modeling to interpret negative-review content. Broader reviews of the field [5] document a shift from lexicon-based and classical machine-learning approaches (Naïve Bayes, SVM, TF-IDF) toward transformer-based methods such as IndoBERT [8], though classical methods remain widely used because of their interpretability and lower computational cost a consideration relevant to large-corpus, cross-sector analysis such as this study's 841,664-review dataset. Conceptually, Google Play Store reviews of the kind analyzed here constitute a large-scale form of electronic word-of-mouth (eWOM); prior work has shown that eWOM information quality shapes consumer trust and decision-making on digital platforms [9], reinforcing the relevance of mining review text as a lens on platform-level trust dynamics, not merely isolated user complaints.

A methodological question in this literature concerns how sentiment ground truth is established. Several studies adopt a rating-derived (proxy) labeling scheme in which reviews rated 4–5 stars are treated as positive, 3 stars as neutral, and 1–2 stars as negative, then validate this proxy against the review text using a supervised classifier [10]. This study follows the same convention, described in Section 2.

1.2 Fintech Adoption, Trust, and Behavioral Barriers

The Technology Acceptance Model (TAM) [11] and its extension, the Unified Theory of Acceptance and Use of Technology (UTAUT) [12], propose that perceived usefulness, perceived ease of use, and effort expectancy jointly determine technology adoption and continued use intention. In fintech contexts specifically, trust and perceived risk around the safekeeping of funds function as an additional barrier beyond the core TAM/UTAUT constructs, since fintech applications require users to entrust a third party with monetary balances rather than merely exchanging information. A TAM-based survey of Indonesian Generation Z e-wallet users found that, alongside perceived usefulness and perceived ease of use, perceived security significantly shaped behavioral intention to use e-wallets [13], directly paralleling the assurance/fund-safety theme identified as the most sector-differentiating complaint category in the present study's topic modeling. Indonesian studies of fintech P2P lending [14] similarly document that public discourse around fintech lending is shaped by concerns over data protection, personal-data misuse, and illegal-lending practices concerns that plausibly extend to e-wallet balance security. A literature review of customer experience in fintech [15] similarly identifies perceived value, customer support, assurance, speed, and perceived company innovation as key determinants of fintech customer experience and, in turn, customer loyalty intention. These determinants map closely onto the complaint themes identified in the present study transactional and login failures (speed/ease of use), balance and fund-safety concerns (assurance), and KYC upgrade friction (support/ease of use) reinforcing that assurance- and trust-related themes are central to fintech user experience across both qualitative literature synthesis and large-scale text-mining approaches. This study contributes text-mining evidence toward this literature by empirically identifying whether and around which specific themes fintech e-wallet users express lower satisfaction than users of non-financial digital platforms.

1.3 Topic Modeling for Complaint-Theme Discovery

Non-negative matrix factorization (NMF) [16] and Latent Dirichlet Allocation (LDA) [17] are the two most widely used unsupervised topic-modeling techniques for short, informal text such as app reviews. NMF was selected for this study because it produces deterministic, non-probabilistic factorizations that tend to yield more coherent and interpretable topics on short documents with sparse TF-IDF representations [16], a property well suited to the brief, informal Indonesian-language reviews analyzed here.

2. Materials and Methods

This study follows a seven-step research workflow, summarized in Figure 1 and detailed in Sections 2.1–2.5: (1) data collection from eight Indonesian digital-platform applications on Google Play Store; (2) text preprocessing; (3) rating-derived sentiment labeling; (4) validation of the sentiment labels using a TF-IDF and Logistic Regression classifier; (5) NMF topic modeling of negative reviews per sector; (6) non-parametric statistical testing (Kruskal-Wallis and Mann-Whitney U) to compare sectors; and (7) interpretation of the cross-sector findings, presented in Sections 3–4 [18].

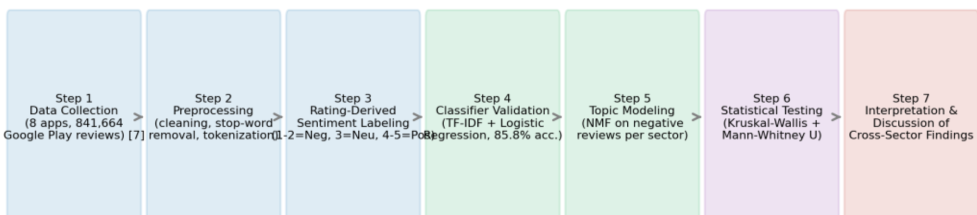

Figure 1. Research methodology framework (seven-step workflow).

2.1 Data Source and Sample

The dataset comprises Google Play Store reviews for eight Indonesian mobile applications, scraped and published for sentiment-analysis research on the Kaggle platform [7]: DANA and OVO (fintech e-wallets), Blibli, Bukalapak, and Tokopedia (e-commerce), Gojek (on-demand transportation and delivery), Ruang Guru (education technology), and Traveloka (online travel). After removing records with missing review text or invalid ratings, 841,664 reviews remained, spanning review dates from 2013 to early 2025. Table 1 summarizes the sample by application and sector.

App	Sector	N	Mean Rating	SD
DANA	Fintech – E-Wallet	106,465	2.38	1.68
OVO	Fintech – E-Wallet	83,182	2.33	1.70
Gojek	On-Demand Services	116,016	2.89	1.78
Blibli	E-Commerce	116,884	4.05	1.43
Bukalapak	E-Commerce	90,147	3.85	1.67

Tokopedia	E-Commerce	71,242	3.14	1.83
Traveloka	Travel & Tourism	145,890	4.27	1.30
Ruang Guru	Education Technology	111,838	4.51	1.16

Table 1. Sample size and rating descriptives by application and sector (N = 841,664).

2.2 Preprocessing

Review text was case-folded, stripped of URLs and non-alphabetic characters, and tokenized on whitespace. A curated Indonesian stop-word list covering function words, common colloquial fillers (e.g., "gak", "udah", "sih"), and platform-generic terms (e.g., "aplikasi") was applied, and tokens shorter than three characters were removed. For computationally intensive steps (classifier training and topic modeling), a stratified sample of up to 3,000 reviews per application per sentiment class (71,126 reviews total) was drawn; descriptive statistics and the Kruskal-Wallis test in Section 3 use the complete 841,664-review dataset.

2.3 Sentiment Labeling and Validation

Following the rating-derived proxy convention used in prior app-review sentiment research [10], reviews rated 1–2 stars were labeled negative, 3 stars neutral, and 4–5 stars positive. To validate that this proxy reflects genuine sentiment content in the review text rather than being an arbitrary numeric split a binary classifier (excluding the neutral class) was trained using TF-IDF features (unigrams and bigrams, 6,000 features, minimum document frequency 5) and Logistic Regression (C = 5, max_iter = 1000) on an 80/20 stratified train-test split of the balanced sample.

2.4 Topic Modeling

For each sector, negative reviews (1–2 stars) in the stratified sample were vectorized with TF-IDF (2,000 features, unigrams and bigrams, minimum document frequency 5) and decomposed into four topics using NMF (random_state = 42, 400 iterations). The ten highest-weighted terms per topic were extracted and manually labeled by the authors based on semantic coherence, following standard practice in topic-modeling interpretation [4], [13].

2.5 Statistical Testing

Because star ratings are ordinal and non-normally distributed (confirmed by inspection of the rating distributions in Table 1), a Kruskal-Wallis H test was used to test for overall differences in rating distributions across the five sectors, with epsilon-squared (ε^2) reported as an effect-size measure. Pairwise comparisons between the fintech e-wallet sector and each other sector were then conducted using Mann-Whitney U tests with a Bonferroni-corrected significance threshold ($\alpha = 0.05/4 = 0.0125$) to control for multiple comparisons. All statistical analyses were performed in Python 3.12 using pandas, scikit-learn, and SciPy.

3. Results

3.1 Sentiment Classifier Validation

The TF-IDF + Logistic Regression classifier achieved 85.8% accuracy and a macro F1-score of 0.858 on the held-out test set (n = 9,483), indicating that the rating-derived sentiment labels are strongly reflected in review text content and supporting their use as a valid proxy for subsequent analysis. Table 2 reports class-level performance.

Class	Precision	Recall	F1-score	Support
Negative	0.849	0.872	0.861	4,776
Positive	0.867	0.843	0.855	4,707
Accuracy			0.858	9,483

Table 2. Binary sentiment classifier performance (TF-IDF + Logistic Regression).

Inspection of the highest-weighted terms associated with each class (Table 3) shows that positive-sentiment terms center on ease of use, gratitude, and helpfulness (e.g., "mudah" [easy], "membantu" [helpful], "terimakasih" [thank you]), while negative-sentiment terms center on disappointment, product/service failure, and account or refund problems (e.g., "kecewa" [disappointed], "buruk" [bad], "refund", "blokir" [blocked])   providing face validity for the classifier and the underlying rating-derived labels.

Sentiment	Top discriminative terms
Positive	mudah, membantu, cepat, terimakasih, memudahkan, keren, bagus aplikasinya, luar biasa
Negative	kecewa, buruk, jelek, refund, blokir, mengecewakan, sampah, uninstal, mempersulit

Table 3. Top discriminative terms per sentiment class (Logistic Regression coefficients).

3.2 Cross-Sector Differences in User Satisfaction (RQ1)

Figure 2 presents mean star ratings by sector. Education Technology (M = 4.51) and Travel & Tourism (M = 4.27) show the highest average satisfaction, followed by E-Commerce (M = 3.75). On-Demand Services (M = 2.89) and, most notably, Fintech – E-Wallet (M = 2.35) show markedly lower average ratings. A Kruskal-Wallis test confirmed that these differences are statistically significant, $H(4) = 160{,}561.5$, $p < .001$, with a small-to-moderate effect size ($\varepsilon^2 = 0.191$).

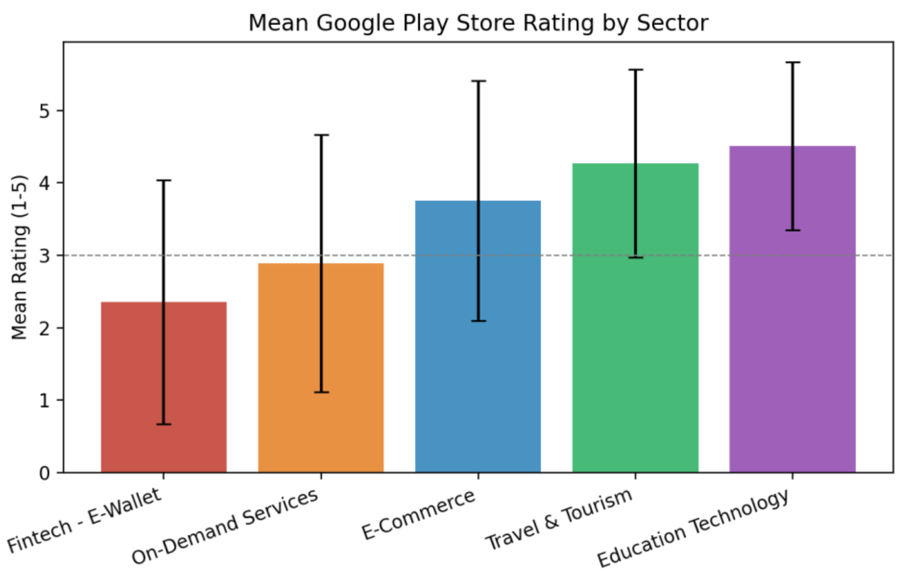

Figure 2. Mean Google Play Store rating by sector (error bars = ±1 SD).

Pairwise Mann-Whitney U tests comparing the fintech e-wallet sector against each other sector were all statistically significant at the Bonferroni-corrected threshold ($\alpha = 0.0125$; all $p < .001$), confirming that fintech e-wallets' lower satisfaction is not attributable to chance variation relative to any individual comparison sector.

3.3 Sentiment Distribution by Sector

Figure 3 shows the proportion of negative, neutral, and positive reviews by sector. The fintech e-wallet sector has the highest share of negative reviews (63.4%), more than six times the share observed in Education Technology (9.6%) and roughly five times that of Travel & Tourism (12.7%). On-Demand Services shows an intermediate, near-evenly-split pattern (48.8% negative, 42.5% positive).

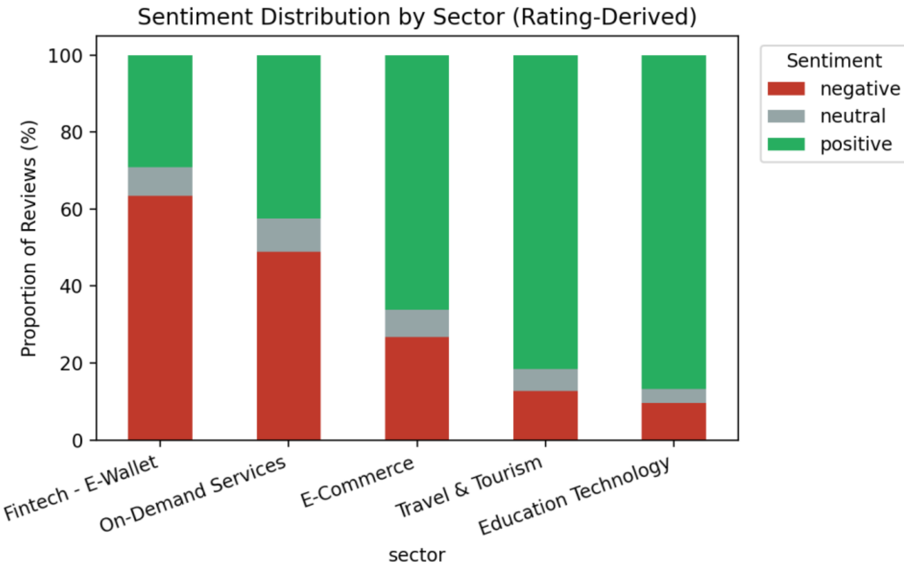

Figure 3. Sentiment distribution (%) by sector, derived from star ratings.

3.4 Topic Modeling: Dominant Complaint Themes (RQ2)

NMF topic modeling of negative reviews within each sector surfaced distinct thematic patterns, summarized in Table 4.

Sector	Dominant negative-review themes (interpreted)
Fintech – E-Wallet	(1) Failed balance top-up/transfer; (2) Premium/KYC upgrade friction (ID verification failure); (3) Login/update/connectivity bugs; (4) Balance or funds disappearing unexpectedly (trust/security concern)
On-Demand Services	(1) Driver/order cancellation; (2) GoPay balance/account issues; (3) Forced app-update bugs; (4) Rising fares and service fees
E-Commerce	(1) Delayed delivery/transaction disputes; (2) Shipping-cost and promo dissatisfaction; (3) App update/login errors; (4) Wallet/payment integration errors
Education Technology	(1) Content/tutor quality concerns; (2) Subscription pricing complaints; (3) App download/technical issues; mixed satisfaction signals
Travel & Tourism	(1) Refund and hotel-booking complaints; (2) Perceived decline in app quality over time; (3) General app-quality complaints/uninstall intent; (4) High ticket/flight prices

Table 4. Interpreted complaint themes from NMF topic modeling of negative reviews, by sector.

These text-mined complaint themes for the fintech e-wallet sector also connect to prior survey-based evidence on OVO specifically: a PLS-based study of 175 OVO users found that transaction speed and top-up facility quality each had a significant positive effect on usage decisions [19]. The prevalence of failed top-up and transfer complaints in Topic 1 of the present analysis (Table 4) is consistent with this prior finding in the opposite direction where survey respondents identified transaction speed and top-up reliability as significant positive drivers of continued OVO usage, the negative reviews analyzed here show that failures in precisely these areas (delayed top-ups, failed transfers) are a dominant source of dissatisfaction, triangulating survey-based and review-based evidence around the same underlying service dimensions.

Notably, the fintech e-wallet sector is the only sector in which a distinct topic centers on the unexpected loss or disappearance of monetary balance ("saldo hilang", "tiba-tiba" [suddenly]) together with account-blocking language, alongside a separate topic specifically concerning identity-verification (KTP/KYC) upgrade failures themes with no direct counterpart in the other four sectors, where complaints instead concentrate on pricing, delivery delays, and app-update bugs.

4. Discussion

The findings provide three main contributions relative to RQ1–RQ3. First, addressing RQ1, cross-sector comparison confirms that user dissatisfaction is not uniform across Indonesian digital platforms: fintech e-wallets and, to a lesser extent, on-demand services show substantially lower satisfaction than e-commerce, travel, and education-technology platforms, a pattern effect-size analysis ($\varepsilon^2 = 0.191$) suggests is meaningful in magnitude, not merely a byproduct of the very large sample size. Second, addressing RQ2, topic modeling shows that the content of dissatisfaction not merely its intensity differs by sector: pricing and delivery-timeliness concerns dominate e-commerce and on-demand complaints, whereas fintech e-wallet complaints uniquely combine transactional failure with fund-safety and identity-verification friction.

Third, addressing RQ3, this fund-safety and KYC-friction pattern is consistent with, and extends, TAM/UTAUT-based fintech adoption research [11], [12] and prior Indonesian fintech studies documenting public concern over data protection and fund security in P2P lending [14]. Where TAM/UTAUT typically model trust and perceived risk as antecedents measured through survey instruments, the present analysis offers converging textual evidence drawn from real post-adoption user complaints rather than pre-adoption intention surveys that trust-related friction (balance disappearance, KYC upgrade failure) remains a salient concern even among users who have already adopted and continue to use e-wallet applications. From a behavioral-finance perspective, the intensity of language associated with these complaints (e.g., "kecewa", "tiba-tiba", "hilang") is consistent with loss aversion: unexpected loss of accessible funds appears to generate disproportionately negative sentiment relative to comparably inconvenient but non-monetary failures (e.g., app update bugs) observed in other sectors.

This platform-level view also complements individual-level evidence on digital-wallet financial satisfaction: a structural equation modeling study of Jakarta digital-wallet users found that financial knowledge and financial behavior significantly predict financial satisfaction, while financial attitude alone does not [20]. Taken together with the present findings, this suggests that fintech financial satisfaction is jointly shaped by user-side factors (financial literacy and money-management behavior) and platform-side factors (transactional reliability and fund-safety assurance identified here) implying that improving e-wallet satisfaction likely requires interventions at both levels, rather than platform UX improvements alone.

Notably, this study's negative findings for standalone e-wallets contrast with survey-based evidence from bank-affiliated digital payment services in Indonesia: a regression-based study of BRImo (a mobile-banking-linked digital payment feature) among MSMEs in Bangkalan Regency found a significant positive effect of digital payment adoption on financial satisfaction [21] [22]. Read together, this suggests that fintech satisfaction outcomes may depend on sub-type bank-affiliated payment features embedded within an established institutional relationship (e.g., BRImo) versus standalone, non-bank e-wallets (e.g., DANA, OVO) that require users to independently build trust in a new financial intermediary. This distinction offers a promising direction for future comparative research and nuances the present study's cross-sector conclusions: the relevant contrast may be institutional affiliation and trust transfer, not merely 'fintech versus non-fintech.'

These findings carry managerial implications for fintech e-wallet providers: prioritizing engineering and customer-support resources toward transaction-failure transparency, communicative KYC/upgrade workflows, and rapid resolution of fund-safety complaints may yield outsized satisfaction gains relative to general app-quality investments, given that fund-safety themes are the most sector-differentiating complaint category identified. For the broader Management Information Systems literature, the results illustrate the value of large-scale, naturally occurring review text as a complement to survey-based technology-acceptance research, particularly for capturing post-adoption friction that pre-adoption intention models do not directly observe.

Several limitations should be noted. The sentiment label is a rating-derived proxy rather than human-annotated ground truth, though its 85.8% classifier validation accuracy is consistent with comparable studies [2], [3], [10]. The dataset covers two e-wallet applications (DANA, OVO) rather than the full population of licensed Indonesian fintech providers, and does not include peer-to-peer lending applications specifically, so findings should be generalized to the broader P2P lending sub-sector with caution. Topic labels were assigned through researcher interpretation of NMF term weights rather than independent multi-coder validation, a common practice in this literature [4], [16] but one that introduces subjectivity. Finally, the cross-sectional design cannot establish causal direction between specific incidents (e.g., a KYC policy change) and satisfaction trends over time.

5. Conclusions

This study applied text mining to 841,664 Google Play Store reviews across eight Indonesian digital platform applications spanning five sectors, combining a validated rating-derived sentiment classifier, NMF topic modeling, and non-parametric statistical testing. The analysis finds statistically significant, and substantively meaningful, cross-sector differences in user satisfaction, with the fintech e-wallet sector showing the lowest satisfaction (63.4% negative reviews) driven by a distinctive combination of transactional failure, fund-safety trust concerns, and identity-verification friction not observed to the same degree in e-commerce, on-demand, travel, or education-technology platforms. These findings extend fintech adoption and trust literature with large-scale textual evidence and offer actionable priorities for fintech user-experience design.

Future research could extend this work using transformer-based Indonesian language models such as IndoBERT [8] for finer-grained sentiment and emotion classification, incorporate peer-to-peer lending applications specifically to test whether the fund-safety theme generalizes beyond e-wallets, and adopt a longitudinal design to test whether satisfaction trends shift following specific regulatory or product changes (e.g., OJK policy updates on fintech lending [1], [14]).

6. Acknowledgments

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7. Author Contributions

Conceptualization, A.D.B. and E.E.; Methodology, E.E.; Formal Analysis, E.E.; Data Curation, E.E.; Writing Original Draft Preparation, E.E.; Writing – Review and Editing, A.D.B. and E.E.; Supervision, A.D.B. All authors have read and agreed to the published version of the manuscript.

8. Conflict of Interest

The authors declare no conflict of interest.

9. Data Availability Statement

The dataset analyzed in this study is publicly available on Kaggle at https://www.kaggle.com/datasets/rezkyyayang/reviews-of-indonesian-app-startups-on-playstore [7]. Analysis code and derived outputs are available from the corresponding author upon reasonable request.

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