The Influence of Personalized Marketing and User Experience on User Loyalty on the Spotify Platform

Nanda Azha Fazira[1], Rita Eka Setianingsih[2]
[1]Management, Institut Bisnis dan Informatika Kwik Kian Gie, Jakarta, Indonesia
[2]Management, Institut Bisnis dan Informatika Kwik Kian Gie, Jakarta, Indonesia

Abstract. The digital music industry faces growing challenges in retaining customer loyalty amid intense competition among streaming platforms and overwhelming content volumes. This study examines the influence of personalized marketing and user experience on loyalty among active Spotify users in Indonesia, an emerging digital market characterised by high internet penetration (approximately 79%) and rapid streaming adoption. Using a quantitative, post-positivist approach, 107 active Spotify users were selected through purposive sampling. Data were collected via structured Likert-scale questionnaires and analysed using multiple regression following logarithmic transformation to satisfy normality assumptions. Results indicate that both variables positively and significantly influence user loyalty. The regression coefficient for personalized marketing was 0.397 ($p = 0.000$) and for user experience was 0.221 ($p = 0.033$), with both coefficients interpreted as elasticities within the log-linear model. Jointly, these predictors account for 36.0% of the variance in user loyalty (Adjusted $R^2 = 0.360$, F-test $p < 0.001$). The dominance of personalized marketing over user experience suggests that in a content-commoditised environment, algorithmic curation constitutes the primary loyalty differentiator, while user experience functions as an essential functional substrate. These findings highlight the strategic importance of AI-driven content curation and seamless interface design in fostering long-term user retention on digital music streaming platforms.

Keywords: personalized marketing; user experience; user loyalty; Spotify; digital music streaming; Indonesia

1 Introduction

The global music industry has undergone a fundamental structural transformation, shifting from ownership-based consumption toward access-based streaming. Streaming now accounts for approximately 69% of recorded music revenues worldwide, with over 750 million paid subscriptions globally (IFPI, 2023). Within this ecosystem, platforms such as Spotify, Apple Music, and YouTube Music function as the primary mediators of music consumption behaviour, competing intensely for user attention and long-term loyalty.

[1]Corresponding author: nandaazhafazira22@gmail.com

This transformation is particularly pronounced in emerging digital markets such as Indonesia, where internet penetration has reached approximately 79% of the population, accelerating the uptake of streaming services (APJII, 2023). With a population exceeding 270 million and a rapidly expanding urban middle class, Indonesia represents one of the largest and fastest-growing streaming markets in Southeast Asia. Among available platforms, Spotify dominates user preference through its freemium model combining ad-supported and premium subscription access, as well as its highly developed algorithmic curation capabilities.

Despite this growth, content overload presents a critical structural challenge. With catalogues exceeding 100 million tracks, users face decision fatigue—wasting time searching rather than listening. This paradox of choice adversely affects user experience and increases platform-switching behaviour (Iyengar & Lepper, 2000). To address this, platforms increasingly rely on AI-driven personalized marketing and optimised user experience (UX). Personalized marketing transcends traditional segmentation by using machine learning to curate content based on behavioural patterns, listening histories, and inferred preferences. UX encompasses usability, accessibility, and emotional appeal—dimensions that collectively shape user perception and engagement.

The theoretical foundation of this study rests on two complementary frameworks. Personalized marketing is conceptualised through the Five Promises of Personalization (Abraham & Edelman, 2024), which frames algorithmic curation as a multi-dimensional construct encompassing user empowerment, preference recognition, temporal relevance, content display, and emotional resonance. User experience is operationalised through Morville (2004) UX Honeycomb model, which identifies seven dimensions—useful, usable, preferable, findable, accessible, credible, and valuable—as the determinants of perceived platform quality. These two constructs are hypothesised to jointly and independently predict user loyalty, as conceptualised by Oliver (1999).

While prior research has examined digital customer experience and satisfaction independently, empirical investigation into the synergistic effects of personalized marketing and UX on user loyalty in music streaming contexts—particularly in emerging markets—remains limited. Most existing studies focus on Western or developed-market populations, leaving a gap concerning how Indonesian users, who exhibit distinct digital consumption patterns and economic constraints, respond to personalisation and platform design. This study addresses that gap by examining how these two constructs, individually and together, influence user loyalty on Spotify among Indonesian users. The novelty of this study lies in its simultaneous examination of personalized marketing and user experience as dual predictors within an emerging market streaming context, contributing empirical evidence to the intersection of digital marketing, consumer behaviour, and platform service research.

The following hypotheses are proposed:

1. H1: Personalized marketing has a significant positive effect on user loyalty on the Spotify platform.
2. H2: User experience has a significant positive effect on user loyalty on the Spotify platform.

2 Method

2.1 Design

This study employed a quantitative approach grounded in a post-positivist paradigm, operationalised through an associative causal survey design. The design was intended to measure directional relationships between two independent variables—Personalized

Marketing (X1) and User Experience (X2)—and the dependent variable User Loyalty (Y)—within the operational context of the Spotify platform. Rather than employing experimental controls, a cross-sectional, naturalistic design was adopted using structured self-administered questionnaires.

2.2 Participant/ Population and Sample

The theoretical population comprised all active Spotify users, including both free-tier and premium-tier subscribers in Indonesia. Due to the population's vast and geographically dispersed nature, a non-probability purposive sampling method was applied. Participants were required to: (1) be active Spotify users regardless of subscription tier; (2) have used the platform continuously for a minimum of three months; and (3) actively engage with core personalisation features such as algorithmic playlists and content discovery tools.

Sample size was determined following the guideline proposed by Hair et al. (2022), which recommends a minimum of five respondents per indicator item. With a total of 16 indicator items across the three constructs, the minimum required sample size was 80 respondents. Following screening, valid data were collected from 107 qualified respondents, exceeding this threshold. The demographic profile is presented in Table 1.

Table 1. Demographic Profile of Respondents (N = 107)

Characteristic	Category	n	%
Age	17–20 years	25	23.36
	21–25 years	53	49.53
	26–30 years	22	20.56
	> 30 years	7	6.54
Gender	Male	47	43.93
	Female	60	56.07
Occupation	Student	51	47.66
	Employee	33	30.84
	Entrepreneur	19	17.76
	Homemaker	4	3.74
Subscription	Premium	59	55.14
	Free	48	44.86
Usage Duration	3–6 months	8	7.48
	6 months–1 year	15	14.02
	1–3 years	33	30.84
	> 3 years	51	47.66
Usage Frequency	Daily	65	60.75
	Several times/week	38	35.51
	Several times/month	4	3.74

Note. n = number of respondents; % = percentage of total sample (N = 107).

The sample was predominantly young: approximately 73% were under 25 years old and 47.66% were students, reflecting broader Generation Z streaming trends in Indonesia. Nearly half the sample (47.66%) had used Spotify for over three years, and 96.26% accessed the application daily or several times per week, ensuring longitudinal familiarity with algorithmic curation and the platform interface.

2.3 Instrument/ Data collection

Data were collected via a structured, self-administered electronic questionnaire distributed through Google Forms using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The questionnaire was disseminated through social media channels and personal networks targeting Spotify users who met the three inclusion criteria.

Personalized Marketing (X1) was operationalised using the Five Promises of Personalization framework (Abraham & Edelman, 2024), measuring five dimensions adapted to the Spotify context: Empower Me (perceived user control over recommendations), Know Me (platform understanding of individual preferences), Reach Me (temporal accuracy of suggestions), Demonstrate (content display personalisation), and Delight Me (emotional resonance of algorithmic outputs).

User Experience (X2) was measured using Morville (2004) UX Honeycomb model across seven dimensions adapted to the Spotify platform: Useful, Usable, Preferable, Findable, Accessible, Credible, and Valuable.

User Loyalty (Y) was assessed using four indicators adapted from Oliver (1999): repeat usage intent, cross-product engagement (e.g., Spotify Podcasts), referral intent, and switching resistance. All items across the three constructs were adapted to the Spotify context.

2.4 Data Analysis

Data were analysed using IBM SPSS version 24. Construct validity was assessed via Pearson Product Moment Correlation; reliability via Cronbach’s Alpha (threshold $\alpha > 0.70$). Descriptive statistics characterised sentiment profiles across constructs.

Prior to regression modelling, three classical assumption tests were conducted: normality (one-sample Kolmogorov–Smirnov test), multicollinearity (Variance Inflation Factor [VIF] and Tolerance), and heteroskedasticity (Glejser test). An initial normality violation was detected and corrected through natural logarithm transformation, applied in order to satisfy the normality assumption required for OLS regression. This yielded the following log-linear regression model:

$$In\ Y = \beta 0 + \beta 1\ In\ X1 + \beta 2\ In\ X2 + \varepsilon \tag{1}$$

In this log-linear specification, the regression coefficients are interpreted as elasticities, allowing percentage-change (elasticity) relationships to be derived directly: a 1% change in an independent variable is associated with a β% change in user loyalty, holding all other variables constant. Partial effects were tested using t-tests; joint model significance was assessed via the F-test. Adjusted R^2 determined overall explanatory power.

3 Results and Discussion

3.1 Results

3.1.1 Validity and Reliability

All indicator items demonstrated strong construct validity, with Pearson correlation coefficients ranging from 0.428 to 0.879, all exceeding the critical value of $r = 0.361$. Cronbach's Alpha confirmed high internal consistency across all three constructs: Personalized Marketing ($\alpha = 0.740$), User Experience ($\alpha = 0.865$), and User Loyalty ($\alpha = 0.713$)—all surpassing the 0.70 threshold (Nunnally, 1978).

3.1.2 Descriptive Statistics

Descriptive statistics revealed a strong positive central tendency across all constructs, reflecting high overall satisfaction with the Spotify platform (Table 2). Within Personalized Marketing (M = 4.25), perceived user autonomy (Empower Me) scored highest (M = 4.50), while temporal recommendation accuracy (Reach Me) scored lowest (M = 4.05), suggesting room for improvement in real-time contextual curation. In User Experience (M = 4.31), utilitarian efficacy (Useful) scored highest (M = 4.40). For User Loyalty (M = 4.18), long-term retention intent scored highest (M = 4.28), while active referral behaviour scored lowest (M = 4.03).

Table 2. Descriptive Statistics by Construct

Construct	Mean	95% CI	Interpretation
Personalized Marketing (X1)	4.25	4.09–4.40	Strongly Agree
User Experience (X2)	4.31	4.16–4.46	Strongly Agree
User Loyalty (Y)	4.18	4.02–4.34	Agree

Note. CI = Confidence Interval. All items rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

3.1.3 Classical Assumption Testing

The initial Kolmogorov–Smirnov test returned Asymptotic Significance = 0.000, indicating non-normality—a ceiling effect typical in high-satisfaction samples. Following logarithmic transformation, the post-transformation test produced a statistic of 0.060 (Asymptotic Significance = 0.200), confirming that the normality assumption was satisfied.

Multicollinearity tests confirmed structural independence between predictors, with both X1 and X2 producing VIF = 1.685 and Tolerance = 0.593, well within acceptable thresholds (VIF < 10; Tolerance > 0.10). The Glejser heteroskedasticity test returned significance values of 0.571 (X1) and 0.485 (X2), both exceeding the 0.05 alpha level, confirming homoskedastic error variance.

3.1.4 Regression and Hypothesis Testing

After validating all classical econometric assumptions, the estimated regression equation was:

$$In\ Y = 0.441 + 0.397\ In\ X1 + 0.221\ In\ X2 \tag{2}$$

Table 3. Multiple Regression Coefficients

Variable	B	Std. Error	t	Sig.
Constant	0.441	0.131	3.364	0.001
Personalized Marketing (X1)	0.397	0.097	4.102	0.000
User Experience (X2)	0.221	0.102	2.166	0.033

Note. B = unstandardised regression coefficient (interpreted as an elasticity in the log-linear model); t = t-statistic for the partial test; Sig. = two-tailed p-value.

Partial t-tests confirmed that both hypotheses were supported. For H1, a 1% increase in Personalized Marketing quality is associated with a 0.397% increase in User Loyalty, holding User Experience constant ($t = 4.102$, $p = 0.000$). H1 is therefore supported. For H2, a 1% improvement in User Experience is associated with a 0.221% increase in User Loyalty, holding Personalized Marketing constant ($t = 2.166$, $p = 0.033$). H2 is therefore supported. The simultaneous F-test produced $F = 27.665$ ($p < 0.001$), confirming the joint model's statistical significance.

Table 4. Model Summary

Model	R	R Square	Adjusted R Square
1	0.611	0.373	0.360

The Adjusted R^2 of 0.360 indicates that the two predictors jointly explain 36.0% of the variance in User Loyalty. This means that approximately 36% of User Loyalty is explained by Personalized Marketing and User Experience, while the remaining 64.0% is attributable to exogenous variables not captured in this model, including pricing sensitivity, exclusive content lock-in, perceived audio quality, and social network effects. These unexplained factors are discussed further in Section 4 as important avenues for future research.

3.2 Discussion

The empirical findings confirm the structural importance of algorithmic personalisation and interface design in shaping digital loyalty within the competitive streaming market. Both constructs exert statistically significant positive effects on user loyalty, supporting H1 and H2.

The substantially larger elasticity coefficient for Personalized Marketing ($\beta1 = 0.397$) relative to User Experience ($\beta2 = 0.221$) is theoretically meaningful and practically important. In a content-commoditised environment—where all major streaming platforms offer near-identical catalogues of over 100 million tracks—algorithmic curation has supplanted aesthetic interface design as the primary loyalty differentiator. This finding aligns with the Algorithmic Personalisation Loop framework (Abraham & Edelman, 2024), wherein an algorithm that accurately mirrors a user's behavioural and acoustic preferences fulfils the core dimensions of the Five Promises of Personalization, particularly Know Me and Delight Me. The overwhelming statistical significance ($p = 0.000$) confirms that contemporary users willingly delegate content selection to predictive systems, relieving the cognitive burden of navigating oversized catalogues—consistent with Iyengar & Lepper's (2000) paradox of choice. Personalised data-visualisation campaigns such as Spotify Wrapped further convert passive listeners into active brand advocates, reinforcing loyalty through social proof (Oliver, 1999). These findings are consistent with prior studies demonstrating that AI-driven personalisation significantly improves user engagement and retention on digital platforms (Chung et al., 2020; Melumad & Pham, 2020).

User experience, while producing a smaller coefficient, remains a statistically significant predictor ($p = 0.033$) and a structural prerequisite for loyalty. Drawing on Morville (2004) UX Honeycomb, the findings indicate that core hygiene factors—accessibility, usability, and findability—are non-negotiable retention conditions. Personalisation algorithms, however sophisticated, become operationally inaccessible without a responsive, well-designed interface. User experience thus functions as the functional substrate through which personalisation is delivered and experienced—its absence harms retention, but its presence alone does not drive loyalty. This interpretation aligns with Davis's (1989) Technology Acceptance Model, which posits that perceived usefulness and ease of use are foundational determinants of continued technology adoption. The finding that UX produces a weaker effect than personalisation is consistent with the view that in mature digital markets, UX expectations are largely met across competing platforms, whereas personalisation quality remains a genuine differentiator.

The unexplained 64.0% of loyalty variance underscores the multidimensional nature of streaming retention and represents an important direction for future research. Key exogenous factors likely include pricing elasticity and the freemium trade-off, ethical perceptions of artist royalty structures, exclusive content lock-in strategies (e.g., podcast exclusives), perceived audio quality, and social network effects driving platform adoption through peer recommendation. These dimensions lie beyond this study's scope but represent critical avenues for expanding the explanatory model in future work.

4 Conclusion

This study empirically confirms that both personalized marketing and user experience are significant positive predictors of user loyalty on the Spotify platform among Indonesian users. Personalized marketing exerts the stronger influence ($\beta = 0.397$), underscoring the strategic centrality of AI-driven algorithmic curation for digital retention. User experience, while secondary in magnitude ($\beta = 0.221$), is a non-negotiable functional pillar without which personalisation loses its delivery mechanism.

For platform architects and digital marketing practitioners, these findings translate into clear strategic imperatives: invest in contextually intelligent recommendation systems that capture real-time user intent beyond historical data; enhance user control and transparency over algorithmic inputs to build trust and autonomy; and maintain frictionless, continuously audited interface architectures as platform complexity increases.

This study is subject to several methodological limitations. The purposive, non-probability sample is overrepresented by younger Indonesian users (73% under 25), limiting generalisability to broader demographic profiles. The model explains only 36.0% of loyalty variance, indicating that substantial unexplained factors remain. Cross-sectional data preclude causal inference; observed associations do not establish directionality. Future research should adopt longitudinal panel designs and expanded structural equation models incorporating pricing sensitivity, exclusive content value, perceived audio quality, platform ethics perceptions, and social influence to build a more comprehensive account of consumer retention in global digital media environments.

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