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# Cross-Platform Digital Visibility of Indonesian Musicians: Managerial Implications from Spotify, YouTube, and TikTok

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## Abstract

This study examines the cross-platform digital visibility of Indonesian musicians and derives managerial implications from synchronized public chart data. An exploratory quantitative design was applied to a one-week snapshot ending 27 August 2026. The revised baseline is defined as 30 Spotify track entries rather than 30 unique musicians because repeated artists are present in the retained chart data. Inferential analysis uses 11 tracks that appeared on both Spotify Weekly Indonesia and YouTube Weekly Indonesia. Spotify and YouTube ranks were compared with Spearman correlation, while weekly stream volumes were examined with Pearson correlation, confidence intervals, and sensitivity checks. TikTok sound data were retained as an auxiliary illustration of social discovery. Spotify and YouTube ranks were positively associated (rho = 0.691, p = 0.019), and weekly stream volumes showed a strong positive association (r = 0.894, p < 0.001; 95% CI 0.635 to 0.972). The relationship remained positive after log transformation and leave-one-out checks. Rank gaps nevertheless reveal uneven platform visibility, with "MMG" showing substantially stronger relative visibility on YouTube. The article operationalizes a signed cross-platform rank gap and treats multi-track chart presence as preliminary portfolio breadth rather than longitudinal retention. The contribution is a cautious diagnostic framework for coordinated audience management that separates social discovery, audiovisual visibility, audio consumption, and portfolio breadth without claiming causal audience conversion.
**Keywords:** digital visibility; music management; cross-platform analysis; streaming platforms; Indonesian musicians

## Abstrak

Penelitian ini mengkaji visibilitas digital lintas platform musisi Indonesia dan merumuskan implikasi manajerial dari data chart publik yang diselaraskan pada periode yang sama. Desain kuantitatif eksploratif diterapkan pada snapshot satu minggu yang berakhir 27 Agustus 2026. Baseline direvisi menjadi 30 entri lagu Spotify, bukan 30 musisi unik, karena data chart yang dipertahankan memuat kemunculan berulang dari artis yang sama. Analisis inferensial menggunakan 11 lagu yang muncul bersamaan pada Spotify Weekly Indonesia dan YouTube Weekly Indonesia. Hubungan peringkat diuji dengan korelasi Spearman, sedangkan volume streaming mingguan dianalisis menggunakan korelasi Pearson, interval kepercayaan, dan uji sensitivitas. Data sound TikTok digunakan sebagai ilustrasi tambahan untuk penemuan sosial. Peringkat Spotify dan YouTube berhubungan positif (rho = 0,691; p = 0,019), sedangkan volume streaming mingguan menunjukkan hubungan positif yang kuat (r = 0,894; p < 0,001; IK 95% 0,635 hingga 0,972). Hubungan tetap positif setelah transformasi log dan pemeriksaan leave-one-out. Perbedaan peringkat tetap memperlihatkan visibilitas yang tidak merata, dengan "MMG" memiliki posisi relatif jauh lebih kuat di YouTube. Artikel mengoperasionalkan selisih peringkat lintas platform bertanda dan menempatkan kemunculan beberapa lagu dari artis yang sama sebagai keluasan portofolio awal, bukan retensi longitudinal. Kontribusi penelitian berupa kerangka diagnosis yang berhati-hati untuk manajemen audiens lintas platform dengan memisahkan penemuan sosial, visibilitas audiovisual, konsumsi audio, dan keluasan portofolio tanpa mengklaim konversi audiens secara kausal.
**Kata kunci:** visibilitas digital; manajemen musik; analisis lintas platform; platform streaming; musisi Indonesia

## 1. Introduction

Digital platforms have altered the conditions under which recorded music becomes visible, discoverable, and repeatedly consumed. The central managerial challenge is no longer limited to distributing a track to digital services. Artists and managers must compete for attention inside platform infrastructures that rank, recommend, surface, and recirculate cultural content. Nieborg and Poell (2018) describe platformization as the penetration of platform infrastructures, economic logics, and data systems into cultural production. For music management, this means that visibility is partly produced through interactions among repertoire, audience behavior, interface design, recommendation systems, and platform-specific promotional practices.

Algorithmic visibility is especially important because exposure on a platform is shaped by more than listener demand. Bonini and Gandini (2019) show that music curation combines editorial decisions with algorithmic processes that structure listening agendas. Platform interfaces can also redirect attention after a design change. Rackowitz and Haampland (2025) provide causal evidence that changes in interface salience can alter consumption patterns on Spotify. These findings make visibility an observable management problem: an artist can have strong demand while receiving uneven exposure across different platform environments.

Indonesia offers a strategically relevant context for examining this problem. The Ministry of Creative Economy of the Republic of Indonesia (2026) reported large-scale discovery of Indonesian artists by new Spotify listeners and continued growth in royalty earnings from international audiences. Resmadi (2024) shows that streaming platformization in Indonesia has reorganized relationships among platforms, aggregators, and independent musicians. Sepehr and Maulidina (2026) further place Jakarta within a global platform economy in which local consumption intensity can become commercially important to international music firms. These developments make Indonesian musicians suitable for examining how visibility is distributed across services with different audience practices.

Cross-platform behavior complicates platform-specific interpretations of popularity. Siles et al. (2024) show that listeners discover, explore, and incorporate songs through multiple services and devices. A song may first be encountered in short-form video, become recognizable through audiovisual circulation, and later enter repeated audio streaming. Ta et al. (2026) demonstrate that TikTok and Spotify privilege different popularity patterns, which means that prominence on one service cannot be assumed to reproduce itself elsewhere. The managerial issue is therefore the structure of visibility across platforms rather than the largest number observed on a single platform.

The distinction between discovery and downstream consumption also matters. Arrieta (2025) finds that music creators increasingly negotiate the limits of short-lived virality and seek more durable forms of fandom. Cheng et al. (2026) provide evidence that TikTok exposure can have heterogeneous spillovers to other music services. These studies support a cautious separation between social discovery metrics and consumption metrics. A high level of short-form activity may indicate strong discovery, while the same track can hold a different relative position in audio streaming or video consumption.

Artists consequently perform substantial platform-facing labor. Ng and Gamble (2026) show that contemporary music producers face expectations for self-promotion, social-media activity, and negotiation with platform gatekeeping. In Indonesia, Ismail and Silooy (2026) document the use of collaboration, consistent posting, visual quality, and algorithm-aware strategies by independent musicians on TikTok. Such activity suggests that digital visibility belongs inside artist management rather than being treated as an isolated promotional task. The practical question becomes how managers identify where visibility is concentrated and where the next managerial intervention may be needed.

Existing scholarship provides important explanations of platform power, recommendation, virality, and artist labor, yet evidence remains fragmented by platform. Studies of Spotify often focus on recommendation or interface effects. TikTok research often focuses on social discovery and virality. Indonesian studies have examined streaming governance and local platform dependence. Fewer studies use synchronized observations to compare the relative position of the same Indonesian tracks across Spotify and YouTube while keeping TikTok evidence analytically separate. This leaves a specific gap between platform theory and operational music management.

This article addresses that gap by treating cross-platform visibility as a set of related but non-equivalent dimensions. Social discovery refers to circulation through short-form social content. Search attention refers to active interest that could be observed through search data, although it is not tested here. Audiovisual visibility refers to relative prominence and consumption on YouTube. Audio consumption refers to weekly rank and streams on Spotify. Portfolio breadth refers to the simultaneous presence of more than one track by the same artist within the displayed high-ranking baseline. Retention and persistence are reserved for future longitudinal research because a one-week snapshot cannot establish duration.

The conceptual distinction is important because the same metric should not be assigned identical meaning across platforms. Spotify weekly streams represent audio consumption within a charting system. YouTube weekly streams represent audiovisual consumption within a different system. TikTok high-reach sound activity represents social circulation around sound identifiers that may have multiple variants. Google Trends values are query-relative measures of search interest. Combining these observations without attention to measurement structure could create a composite score that appears precise while obscuring differences in what each platform actually measures.

For that reason, the study uses a layered conceptual framework rather than a deterministic funnel. Figure 1 places social discovery, search attention, audiovisual visibility, audio consumption, and portfolio breadth around the broader problem of cross-platform digital visibility. The framework does not assume that users move through the dimensions in a fixed sequence. It identifies analytically distinct locations where attention can become strong or weak. Retention sits outside the empirical snapshot and requires repeated measurement across time.

Comparability across metrics is therefore a substantive methodological issue rather than a formatting problem. A Spotify stream, a YouTube view, a TikTok sound creation, and a Google Trends index are generated by different user actions and platform rules. Their scales cannot be read as interchangeable units of popularity. The present study responds by comparing like with like wherever inferential testing is performed and by keeping unlike indicators in separate descriptive layers. This measurement discipline is central to the managerial argument because a dashboard becomes misleading when heterogeneous metrics are collapsed before their meaning is understood.

A related issue is the increasing role of artificial intelligence in music discovery. Arenal et al. (2026) identify content discovery and competition as major concerns for artists and users in an AI-intensive streaming environment. As recommendation systems become more adaptive, visibility may change even when the underlying repertoire and marketing budget remain constant. This strengthens the case for repeated cross-platform measurement. Managers need to distinguish changes in audience demand from changes that may reflect platform interface, recommendation logic, or content-surfacing practices.

**Table 1. Conceptual dimensions of cross-platform digital visibility**

| Dimension | Platform/source | Indicator | Status in study | Managerial function |
|---|---|---|---|---|
| Social discovery | TikTok | High-reach sound activity; sound variants | Auxiliary illustration only | Identify socially visible sound circulation |
| Search attention | Google Trends | Relative search-interest index | Conceptual, not tested | Future indicator of active search interest |
| Audiovisual visibility | YouTube | Weekly rank and weekly streams | Measured | Assess relative video-platform visibility |
| Audio consumption | Spotify | Weekly rank and weekly streams | Measured | Assess relative audio-streaming visibility |
| Portfolio breadth | Spotify baseline | Multiple tracks by the same artist in the displayed high-ranking set | Descriptive | Identify multi-track presence in the observed week |
| Retention/persistence | Longitudinal panel | Repeated visibility across weeks | Not measured | Test durability of attention over time |

*Source: author conceptualization based on the literature reviewed in this article.*

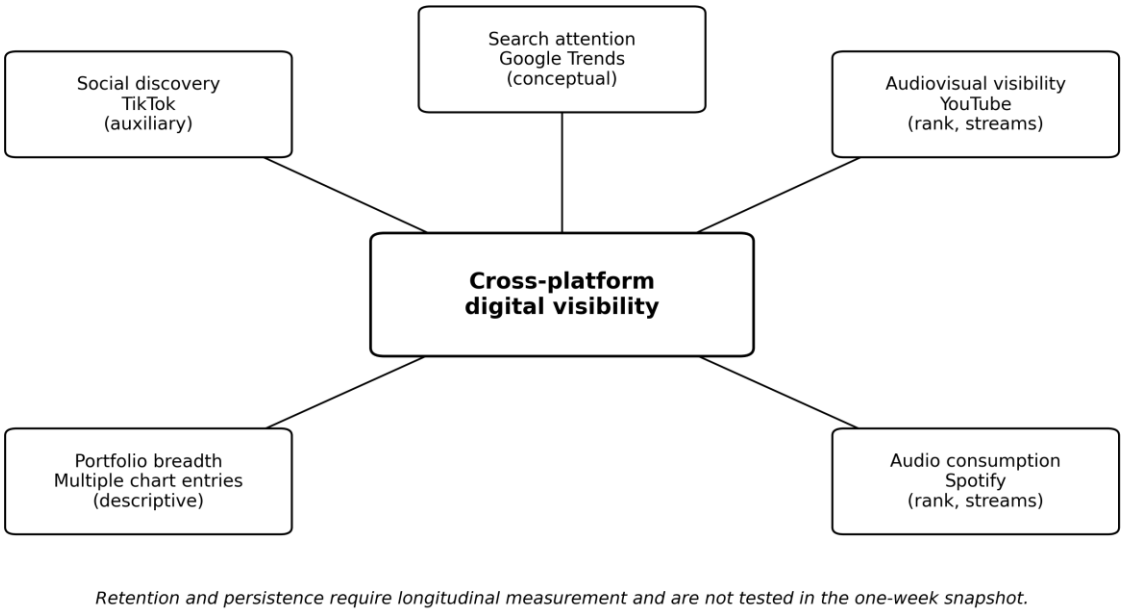



**Figure 1. Cross-platform digital visibility framework**
*Source: author conceptualization based on the literature reviewed in Section 1.*

Within this framework, the first operational diagnostic is the signed cross-platform rank gap. It captures whether a matched track holds a relatively stronger rank on Spotify or YouTube in the same observed week. The second diagnostic is portfolio breadth, defined cautiously as simultaneous multi-track presence in the displayed Spotify baseline. Portfolio breadth is intentionally narrower than retention. It indicates that attention is distributed across more than one active track at a specific time, while persistence would require observing whether that pattern continues across multiple weeks.

The novelty of the article lies in connecting synchronized Indonesian Spotify and YouTube observations with an explicitly defined rank-gap diagnostic, a small-sample robustness analysis, and an auxiliary TikTok illustration while keeping the different measurement systems separate. The contribution is therefore operational and managerial rather than causal. The study asks three questions. RQ1: How strongly are Spotify and YouTube visibility associated among tracks observed on both platforms in the same

week? RQ2: Where do the largest sample-relative cross-platform rank gaps occur, and what do those gaps indicate about the concentration of visibility? RQ3: What managerial implications can be derived when audio consumption, audiovisual visibility, social discovery, and portfolio breadth are treated as distinct dimensions?

## 2. Methods

The study uses an exploratory quantitative design based on public digital trace data. The empirical window is the charting week ending 27 August 2026. A single synchronized week was selected to minimize temporal mismatch between Spotify and YouTube observations and to permit exact track-level pairing. The window should not be interpreted as representative of long-term artist performance. Its purpose is methodological alignment: both platforms are compared within the same observed period so that rank and stream differences are not confounded by using data from different weeks.

The revised sampling description corrects an inconsistency in the earlier manuscript. The retained Spotify working file contains 30 chart entries associated with Indonesian acts, and repeated artists occur within those entries. The baseline is therefore defined as a 30-track snapshot rather than a sample of 30 unique musicians. This revision is necessary because the displayed high-ranking entries include multiple tracks by Tulus and Raim Laode. The unit of observation in the baseline is a track entry. Artist identity is used as a grouping attribute when describing multi-track presence.

The original extraction treated the retained acts as Indonesian musicians. A formal nationality-verification protocol was not archived with the chart extraction, and nationality is not used as a statistical variable in the present analysis. The term Indonesian acts is therefore retained as an operational sampling label from the source dataset rather than a citizenship classification reconstructed after data collection. Future replication should document an explicit origin rule, such as principal-artist nationality or primary market affiliation, and preserve the verification source for every act.

The inferential sample is separate from the 30-track baseline. Eleven tracks were identified as appearing on both Spotify Weekly Indonesia and YouTube Weekly Indonesia for the same week. The analytical unit for correlation is the matched track. Matching was performed manually by artist and track title. Alternate credit conventions, including featured-artist formatting, were reconciled so that the same recording title could be paired across services. The analysis does not infer a match from artist name alone. A track entered the matched sample only when a corresponding title and artist credit could be aligned across the two weekly tables.

Spotify weekly rank and weekly stream counts were obtained from the publicly accessible Kworb historical Spotify Indonesia chart. Kworb (2026a) provides the country-level weekly history used in the source dataset. Spotify (2026) documents that its weekly chart period runs from Friday through Thursday. YouTube weekly rank and stream counts were obtained from the corresponding Kworb Indonesia YouTube insights page. Kworb (2026b) was used because the historical snapshot permits the same track titles to be aligned to the same week.

TikTok is treated as an auxiliary discovery source and is excluded from the inferential Spotify-YouTube model. The source article cross-checked public sound statistics through Chartex. Chartex (2026) reported high-reach activity for more than one sound variant of "Astaga Bercanda" at the time of retrieval. The revised article does not assign a seven-day duration to that observation because the cited Chartex URL contains a 24-hours path and the archived material does not resolve the discrepancy. The counts are therefore described as a retrieval-time snapshot, retained separately by sound variant and used only as an illustration of social discovery.

Google Trends remains in the conceptual framework as a potential measure of search attention. Its values are normalized from 0 to 100 within each query configuration. The source design did not preserve a reproducible multi-batch rescaling procedure with a common anchor term. Google Trends values are therefore excluded from numerical testing. This decision prevents query-relative values from being combined with chart metrics as if all measures shared the same denominator.

Two primary association tests are estimated for the 11 matched tracks. Spearman rank correlation assesses alignment between Spotify rank and YouTube rank without requiring a linear relationship between ordinal positions. Pearson product-moment correlation assesses the relationship between the reported weekly stream volumes. Statistical significance is evaluated at alpha = .05. Approximate 95% confidence intervals for both coefficients are calculated using Fisher z transformation. The interval around Spearman rho is interpreted cautiously because the matched sample is small and the transformation is approximate for rank correlation.

The cross-platform rank gap is defined as $G_i = R_{Spotify,i} - R_{YouTube,i}$, where lower chart numbers indicate stronger positions. A positive value therefore means that the track ranks relatively higher on YouTube than on Spotify. A negative value means that the track ranks relatively higher on Spotify. The absolute gap $A_i = |G_i|$ describes the magnitude of the observed separation without assigning direction. No universal threshold is claimed. For descriptive prioritization inside this sample, an absolute gap at or above the sample 75th percentile is labelled an upper-quartile gap. The observed 75th percentile is 9.5 ranks, so gaps of 10 ranks or more are highlighted as sample-relative large gaps.

Rank normalization was considered because platform chart depths and ranking rules can differ. The archived dataset does not preserve a common denominator that would support defensible percentile normalization across both chart universes. The revised analysis therefore retains the raw signed rank gap as an ordinal diagnostic and explicitly avoids treating a ten-rank difference as equivalent across every possible platform depth. Future replication should capture complete chart depth and use percentile rank or empirical cumulative distribution scaling before comparing gap magnitude across services.

Pearson correlation receives additional sensitivity checks because the matched sample contains two very high-volume tracks. First, weekly stream volumes are log10 transformed and correlated again. Second, the two largest Spotify-volume observations are removed as a conservative influence check. Third, leave-one-out Pearson correlations are calculated by omitting each track in turn. These checks are not substitutes for a larger sample. They indicate whether the direction of association depends entirely on one or two observations. Scatterplot inspection is used descriptively to evaluate the pattern without labelling observations as formal statistical outliers.

Portfolio breadth is also operationalized conservatively. The source article did not retain a complete artist-level catalogue panel across multiple weeks, so a validated catalogue-persistence measure cannot be constructed. The revised article reports only simultaneous multi-track presence in the displayed Spotify top-10 baseline. This top-10 breadth indicator is the number of entries held by the same artist among those ten tracks. It describes the observed distribution of high-ranking entries and does not establish retention, durability, or catalogue conversion.

Confidence intervals are reported because p-values alone can overstate certainty in a small matched sample. The intervals show the range of coefficient values compatible with the observed data under the stated approximation. Sensitivity checks are interpreted in the same way. A stable positive direction across alternative specifications increases confidence that the result is not purely an artifact of one observation, while variation in coefficient size reminds readers that precision remains limited. This approach follows the reviewer request to emphasize estimation uncertainty rather than presenting significance as the sole criterion of evidential strength.

Data validity is supported through synchronized chart periods, exact track-level pairing, retention of source values in tables, and separation of inferential and auxiliary evidence. The study uses aggregated public chart data and does not process individual user records. The analysis is exploratory, and all claims are limited to the observed snapshot. Causal language is avoided because correlation and one-week rank differences cannot establish audience movement from one platform to another.

## 3. Results and Discussion

### 3.1 Results

#### *3.1.1 Spotify baseline and portfolio breadth*

The revised baseline is a 30-track Spotify snapshot rather than 30 unique musicians. Table 2 presents the ten highest-ranked entries available in the source article. This correction resolves the sampling inconsistency identified during review because the table visibly contains repeated artists. Tulus occupies two of the displayed top five positions, while Raim Laode occupies three of the displayed top six. The top-10 subset therefore contains seven distinct principal artist entries across ten tracks when featured-credit formatting is retained as reported.

The repeated entries provide a limited descriptive indicator of portfolio breadth. Raim Laode accounts for three of the ten displayed high-ranking tracks, and Tulus accounts for two. The remaining entries occur once each. This pattern shows that the observed week contains both single-track prominence and multi-track presence. It does not establish long-term catalogue persistence because the analysis does not follow the same artists across multiple weeks.

**Table 2. Leading entries in the Spotify baseline, week ending 27 August 2026**

| Rank | Artist | Track | Weekly streams |
|---|---|---|---|
| 1 | Tulus | Teh Hijau | 12,989,597 |
| 2 | eńau feat. Ari Lesmana | Sesi Potret | 12,973,158 |
| 3 | Raim Laode | Dunia Yang Nanti | 10,248,369 |
| 4 | Raim Laode | Iqro' | 8,664,906 |
| 5 | Tulus | Jatuh Suka | 6,497,307 |
| 6 | Raim Laode | Bersenja Gurau | 6,310,547 |
| 7 | Perunggu | Ini Abadi | 5,981,352 |
| 8 | Ifan Seventeen | Jangan Paksa Rindu (Beda) | 5,776,803 |
| 9 | Kahitna feat. Monita Tahalea | Titik Nadir | 5,590,104 |
| 10 | Nadhif Basalamah | kota ini tak sama tanpamu | 5,450,043 |

*Source: author compilation from Kworb Spotify Weekly Indonesia (Kworb, 2026a).*

#### *3.1.2 Matched Spotify-YouTube visibility and rank gaps*

The same-period matching procedure identified 11 tracks with rank and weekly stream values on both Spotify and YouTube. Table 3 adds the signed rank-gap diagnostic to the original paired observations. A positive gap marks stronger relative rank on YouTube. A negative gap marks stronger relative rank on Spotify. Two tracks, "Teh Hijau" and "Sesi Potret", hold identical positions across the two platforms. Several other tracks differ by five to ten ranks, while a smaller group shows larger separation.

The sample-relative upper-quartile threshold is an absolute gap of 10 ranks. Three tracks meet or exceed that descriptive threshold. "Jatuh Suka" has a gap of -10, indicating a stronger Spotify position. "MMG" has a gap of +16, indicating a stronger YouTube position. "Kangen" has the largest observed gap

at +40. These differences should not be interpreted as standardized performance effects because the analysis uses raw ordinal ranks. They are diagnostic signals showing where relative chart position diverges most strongly inside the matched snapshot.

The distribution of absolute gaps also shows why a single cut-off should not be generalized beyond this sample. The median absolute gap is six ranks, while the upper quartile is 9.5. Most matched tracks therefore sit relatively close to the shared cross-platform ordering, and a smaller subset accounts for the largest asymmetries. This pattern is consistent with the coexistence of a positive overall correlation and song-specific divergence. It also supports using the gap as a triage device for managerial review rather than as a new universal performance score.

**Table 3. Matched Spotify and YouTube performance with signed rank gap**

| Track | Spotify rank | Spotify streams | YouTube rank | YouTube streams | Gap |
|---|---|---|---|---|---|
| Tulus - Teh Hijau | 1 | 12,989,597 | 1 | 11,091,066 | +0 |
| eńau feat. Ari Lesmana - Sesi Potret | 2 | 12,973,158 | 2 | 10,543,978 | +0 |
| Raim Laode - Dunia Yang Nanti | 3 | 10,248,369 | 6 | 6,222,251 | -3 |
| Raim Laode - Iqro | 4 | 8,664,906 | 10 | 4,673,003 | -6 |
| Tulus - Jatuh Suka | 5 | 6,497,307 | 15 | 3,719,446 | -10 |
| Ifan Seventeen - Jangan Paksa Rindu | 8 | 5,776,803 | 13 | 3,786,122 | -5 |
| Kahitna feat. Monita Tahalea - Titik Nadir | 9 | 5,590,104 | 14 | 3,736,443 | -5 |
| Nadhif Basalamah - kota ini tak sama tanpamu | 10 | 5,450,043 | 16 | 3,335,008 | -6 |
| Akbar Chalay - Astaga Bercanda | 20 | 4,335,671 | 11 | 3,964,810 | +9 |
| Naykilla - MMG | 24 | 3,983,451 | 8 | 5,264,071 | +16 |
| Dewa 19 - Kangen | 60 | 2,427,874 | 20 | 2,603,933 | +40 |

*Source: author matching of Spotify data from Kworb (2026a) and YouTube data from Kworb (2026b). Gap = Spotify rank - YouTube rank.*

### *3.1.3 Association tests, uncertainty, and sensitivity*

The matched ranks produce a Spearman correlation of rho = 0.691 with p = 0.0186. The approximate Fisher-transformed 95% confidence interval extends from 0.155 to 0.913. The point estimate indicates a positive association between relative chart positions, while the wide interval reflects substantial uncertainty from the small matched sample. The result is therefore evidence of alignment within the observed week rather than a stable population parameter for Indonesian music.

Weekly stream volumes produce a Pearson correlation of r = 0.894 with p = 0.0002. The 95% Fisher confidence interval ranges from 0.635 to 0.972. This is the strongest inferential association in the study. Figure 2 shows the positive direction visually. The two largest observations, "Teh Hijau" and "Sesi Potret", occupy the upper-right region, while "MMG" sits relatively high on YouTube given its Spotify volume. The visual is used to inspect deviation from the fitted relationship and does not classify formal outliers.

The sensitivity checks reduce concern that the Pearson result is entirely produced by the two largest observations. Log10-transformed weekly streams remain positively correlated at r = 0.837 with p = 0.0013. Removing the two largest Spotify-volume tracks lowers the coefficient to r = 0.691 with p = 0.0393, which remains positive and statistically significant at the .05 level. Leave-one-out Pearson coefficients range from 0.847 to 0.933. The magnitude changes across specifications, yet the direction remains stable in every check.

**Table 4. Cross-platform association tests and sensitivity checks**

| Test | Variables/specification | Coefficient | p-value | 95% CI | Interpretation |
|---|---|---|---|---|---|
| Spearman rank correlation | Spotify rank vs YouTube rank | 0.691 | 0.0186 | 0.155 to 0.913 | Primary rank association |
| Pearson correlation | Raw weekly streams | 0.894 | 0.0002 | 0.635 to 0.972 | Primary volume association |
| Pearson sensitivity | Log10 weekly streams | 0.837 | 0.0013 | - | Reduces scale skew |
| Pearson sensitivity | Remove two largest Spotify-volume tracks | 0.691 | 0.0393 | - | Conservative influence check |
| Leave-one-out Pearson | Omit one matched track at a time | 0.847 to 0.933 | - | - | Direction stable across omissions |

*Source: author calculations from the 11 matched tracks. Confidence intervals use Fisher z transformation and are approximate for Spearman rho.*

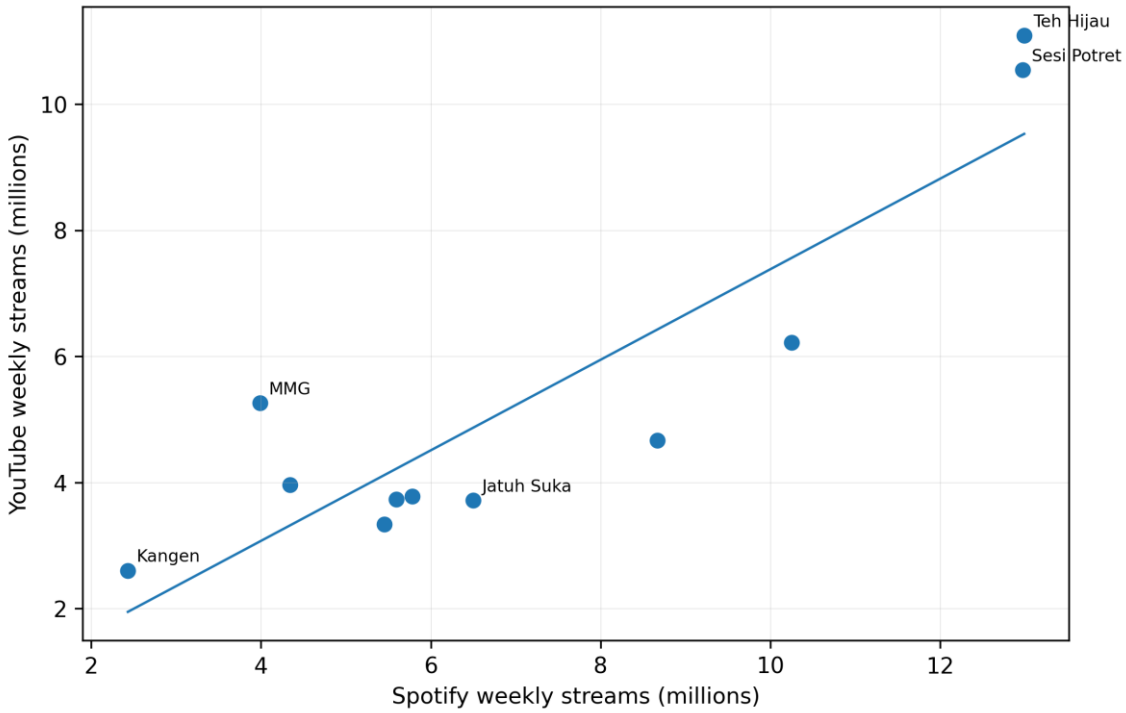



**Figure 2. Spotify and YouTube weekly stream volumes for matched Indonesian tracks**

*Source: author analysis using Spotify values from Kworb (2026a) and YouTube values from Kworb (2026b).*

### *3.1.4 Auxiliary TikTok discovery observation*

The TikTok evidence remains intentionally separate from the inferential analysis. Chartex reported two high-reach sound variants for "Astaga Bercanda" with values of 984 and 945 at the retrieval snapshot. The two values are not summed because sound variants can overlap in exposure and do not represent verified unique users. In the synchronized chart data, the original track ranks 20th on Spotify and 11th on YouTube. The case therefore illustrates that a track can show strong social sound circulation while holding different relative positions on streaming and video charts.

No general conversion rate is inferred from this example. One TikTok case cannot establish that short-form discovery causes or fails to cause streaming consumption. The observation is useful because it demonstrates why discovery metrics and consumption metrics should remain separate in a management dashboard. A longitudinal design would be needed to test whether changes in TikTok activity precede changes in Spotify or YouTube outcomes.

## 3.2 Discussion

### *3.2.1 RQ1: Spotify and YouTube visibility are associated, with substantial uncertainty*

The first research question asks how strongly Spotify and YouTube visibility are associated for tracks observed on both services in the same week. The answer is a positive association in both rank and weekly stream volume. The Pearson result is especially strong, and the sensitivity checks retain a positive direction when stream values are transformed or influential high-volume observations are reduced. The Spearman interval is wider, which is expected from a matched sample of 11 tracks. These results provide preliminary evidence that major tracks in the observed Indonesian snapshot often perform strongly across audio streaming and audiovisual consumption.

The finding is consistent with the cross-platform listening practices described by Siles et al. (2024). Their work emphasizes that songs circulate through interconnected media environments rather than through one isolated service. The present data add a synchronized Indonesian case in which the same track can be observed on two large platforms during the same charting week. The association does not identify which platform leads the other. It simply shows that high visibility often co-occurs across the two measured environments.

The result should also be read alongside platform-specific attention mechanisms. Pachali and Datta (2025) show that platform featuring can steer listener attention within Spotify. YouTube uses different recommendation, search, and audiovisual interaction structures. A cross-platform association can therefore coexist with platform-specific divergence. The strong Pearson coefficient should not encourage managers to treat YouTube as a substitute measurement for Spotify or the reverse. It establishes shared movement in the snapshot, while the rank-gap analysis shows where platform-specific visibility remains uneven.

### *3.2.2 RQ2: Rank gaps identify concentration, not standardized performance effects*

The second research question concerns where large visibility gaps appear. The signed-gap diagnostic makes direction explicit. "Jatuh Suka" is relatively stronger on Spotify, while "MMG" and "Kangen" are relatively stronger on YouTube. These observations are strategically useful because they indicate where an artist or track occupies a different competitive position across services. The gap does not explain why the difference exists. Possible explanations include platform audience composition, audiovisual appeal, recommendation pathways, catalogue age, promotional timing, or differences in chart construction.

The sample-relative threshold provides a reproducible way to identify the largest gaps without pretending that ten ranks has universal meaning. It is based on the upper quartile of absolute gaps in the matched sample. Managers could use the same logic in a larger internal dashboard by ranking standardized gap magnitudes within a defined panel. A stronger future design would normalize ranks to chart depth before comparison. The current article avoids that step because the archived snapshot does not retain a defensible common denominator for both chart universes.

The distinction between correlation and gap is managerially important. Correlation describes whether two platforms tend to move together across tracks. The rank gap describes where a specific track departs from that general alignment. A high overall correlation can therefore coexist with strategically meaningful track-level asymmetry. This dual reading helps managers avoid a common error: interpreting strong market-wide association as evidence that every individual song has balanced visibility.

### *3.2.3 RQ3: From platform metrics to coordinated audience management*

The third research question asks what managerial implications follow when the dimensions are separated. The most defensible implication is diagnostic coordination. A manager can first identify where a track is visible, then decide what type of action is appropriate. Strong Spotify rank with weaker YouTube rank may justify stronger audiovisual packaging or video discovery. Strong YouTube rank with weaker

Spotify rank may justify clearer pathways toward audio listening, playlist strategy, or repeat-streaming cues. These are managerial hypotheses generated by the visibility pattern, not causal effects established by the data.

The auxiliary TikTok case supports the need to preserve that distinction. Arrieta (2025) shows that creators increasingly question whether viral attention automatically produces durable career outcomes. The present "Astaga Bercanda" observation is consistent with the idea that social discovery and downstream consumption can diverge. It does not test conversion. The practical lesson is to track the stages separately so that a manager can see whether strong short-form circulation coincides with stronger audiovisual or audio-platform outcomes in later periods.

For independent Indonesian musicians, the distinction may be especially useful because promotional resources are limited. Ismail and Silooy (2026) document strategic TikTok practices such as collaboration and consistent uploading. A cross-platform dashboard could extend that work by connecting social activity to later platform outcomes without assuming immediate conversion. The manager would monitor discovery indicators, video visibility, audio consumption, and repeated catalogue presence on a common weekly schedule. Decisions could then be based on observed bottlenecks rather than on the largest vanity metric.

### *3.2.4 Portfolio breadth is an observed configuration, while retention remains longitudinal*

The revised treatment of catalogue visibility is deliberately narrower. The one-week baseline supports a claim about portfolio breadth because some artists hold multiple high-ranking tracks at the same time. It does not support a claim about persistence. Tulus appears twice within the displayed top five, and Raim Laode appears three times within the displayed top six. This multi-track presence indicates that audience attention is not confined to one song within the visible top-10 subset.

The distinction matters theoretically and managerially. Shim and Kim (2026) show that recommendation changes can redistribute attention beyond the most prominent tracks. Portfolio breadth is therefore a plausible management concern: a successful entry point may create opportunities for audiences to encounter additional repertoire. The present snapshot can show simultaneous breadth, while only longitudinal data can show whether that breadth persists after release cycles change.

A future portfolio metric could include the number of charting tracks, the share of an artist's chart streams contributed by the leading track, and the number of weeks that older tracks remain visible after a new release. Those measures would convert the present descriptive idea into a repeatable artist-level indicator. The current article stops before that step because the required panel was not part of the source dataset.

### *3.2.5 The Indonesian context and platform dependence*

The Indonesian setting adds more than a geographic case. Resmadi (2024) argues that streaming governance creates dependencies among local artists, aggregators, and global platforms. The visibility diagnostics developed here offer one operational way to examine those dependencies from the management side. An artist who is highly visible on one global service and much weaker on another may be exposed to platform-specific audience structures, recommendation mechanisms, or promotional practices. The diagnosis does not remove dependency, yet it can make the unevenness of platform exposure more visible to managers.

Sepehr and Maulidina (2026) describe Jakarta as strategically positioned in the global music market because of intense digital consumption and platform politics. In such a market, coordinated visibility management can matter for both domestic and international reach. Managers need to know whether a track is primarily strong in audio streaming, video consumption, or social discovery before allocating effort across

content formats and campaigns. The synchronized snapshot supplies a small empirical demonstration of that need.

Prey and Lee (2025) caution against assuming that platformization operates identically across national contexts. The present article follows that caution by avoiding a universal Digital Music Visibility Index from heterogeneous metrics. A composite index may eventually be useful, yet it should be validated with locally relevant indicators, stable normalization, and repeated observations. The first step is to understand the components before combining them.

#### *3.2.6 A conceptual audience-management map, not a tested funnel*

Figure 1 should be interpreted as a management map rather than a tested audience journey. Discovery, search attention, audiovisual visibility, audio consumption, and portfolio breadth can occur in different orders. Users can encounter a song on Spotify first and later search for a video. Others can discover the song on TikTok and never enter an audio-streaming environment. The one-week design cannot observe individual pathways, so the framework organizes managerial questions rather than modelling user-level transitions.

This distinction corrects an overly strong implication in the earlier manuscript. The empirical results suggest that cross-platform transitions should not be assumed and require longitudinal testing. They do not show that a TikTok user becomes a YouTube viewer or Spotify listener. The framework is therefore useful for formulating hypotheses. For example, managers could test whether a rise in social discovery at week t predicts higher YouTube or Spotify outcomes at week t+1 after controlling for releases, playlist exposure, and artist fixed effects.

Such a design would also create a more defensible basis for the proposed Digital Music Visibility Index. The index should be treated as a future validation agenda. It would require standardized indicators, consistent time windows, explicit weights, and tests of reliability and predictive validity. Google Trends could enter the model only after query batches are harmonized with a common anchor term and identical geography and time settings.

#### *3.2.7 Methodological limits and a stronger research agenda*

The strongest limitation is the small inferential sample. Eleven matched tracks are sufficient to demonstrate the calculation and to identify a positive association, yet they are too few for broad generalization. The confidence intervals communicate this uncertainty directly. Sensitivity checks help determine whether the Pearson coefficient is fragile, and the positive direction remains stable. Even so, robustness within a small snapshot is different from external validity across genres, release cycles, artist tiers, and longer periods.

The one-week design is another limitation. It provides synchronization at the cost of temporal depth. No claim can be made about persistence, causal conversion, or lagged spillovers. Future work should collect a fixed panel of artists or tracks weekly for several months. Lagged correlation, panel regression, or event-study designs could then test whether visibility changes on one platform systematically precede changes on another.

Longitudinal work should also record release age, playlist exposure, promotional events, genre, collaboration status, and major platform features when possible. These variables can confound apparent cross-platform relationships. A new release may rise everywhere at once, creating a correlation that reflects common timing rather than movement between platforms. Conversely, a platform-specific placement may produce a temporary gap without any broader audience shift. Controlling for these conditions would make later tests of spillover and conversion more credible.

Third-party aggregators introduce measurement dependence. Kworb is valuable for historical alignment, yet future replication should compare aggregator values with official chart exports where

available and preserve archived retrieval files. TikTok sound identifiers require special care because a song can circulate through multiple official, user-generated, sped-up, slowed, or remixed sounds. A track-level conversion model should define how variants are linked and avoid summing overlapping exposure as unique reach.

The operational category of Indonesian acts also needs stronger documentation in future data collection. The present article retains the sampling label from the source dataset because nationality verification records were not archived. A reproducible panel should state whether classification is based on citizenship, principal artist origin, primary market, label metadata, or another rule. This matters when collaborations include artists from more than one country.

Finally, the raw rank gap is an ordinal diagnostic. It is useful inside the observed sample, but its magnitude depends on chart depth and platform ranking rules. Future studies should capture full chart length and normalize rank to a comparable percentile or empirical cumulative position. That step would make cross-platform gaps more comparable across services and time. It would also allow researchers to distinguish genuine platform asymmetry from mechanical differences in list depth.

#### *3.2.8 Managerial implications by visibility pattern*

The revised framework supports four provisional visibility patterns. A Spotify-dominant track has a negative signed gap and may require stronger audiovisual or social discovery support. A YouTube-dominant track has a positive gap and may benefit from clearer pathways to audio streaming. A balanced track has a small gap and can focus on maintaining coordinated presence. A multi-track artist displays portfolio breadth in the observed baseline and can direct attention from the leading track toward additional repertoire. These patterns are descriptive management categories, not validated market segments.

For practical use, managers could update a simple weekly table containing Spotify rank and streams, YouTube rank and streams, selected TikTok sound indicators, and the number of concurrently visible tracks. The signed gap would highlight platform asymmetry. A time series would then show whether the asymmetry closes, widens, or reverses after a campaign. The value of the framework lies in disciplined comparison: each metric keeps its platform-specific meaning while being read alongside the others.

A managerial dashboard built on this logic should also preserve the date, retrieval source, chart window, and matching rule for every observation. Without those fields, later comparisons can mix different reporting periods or silently change definitions. A simple provenance column can prevent that problem. Managers can then annotate major events such as a release, live performance, playlist placement, viral clip, or paid campaign. Those annotations do not prove causality, yet they create a structured record that can later support stronger evaluation when enough weeks have accumulated.

The framework has a governance implication as well. Platform visibility is partly shaped by systems that artists do not control. Treating every change as a direct reflection of fan preference can therefore lead to poor management decisions. A decline in rank may reflect competitive releases, interface changes, chart eligibility, or recommendation shifts. Managers should read the diagnostic together with contextual information and avoid assigning responsibility to artists or audiences from a single metric. This is especially important for smaller acts whose visibility may be more sensitive to short-term platform exposure.

The approach also discourages a narrow focus on maximizing every platform metric simultaneously. A management team can prioritize the weakest stage relative to campaign objectives. A release already strong in Spotify consumption may not need more audio-focused promotion if its audiovisual discovery is weak. A socially visible sound may need better artist recognition and direct links to the full recording. A broad portfolio may justify retention-oriented communication around the artist rather than one track. These decisions remain hypotheses until they are evaluated with longitudinal data.

**Table 5. Provisional managerial interpretation of observed visibility patterns**

| Pattern | Observed diagnostic | Interpretation | Managerial use |
|---|---|---|---|
| Spotify-dominant | Negative signed rank gap | Stronger relative Spotify position | Test audiovisual and social-discovery support |
| YouTube-dominant | Positive signed rank gap | Stronger relative YouTube position | Test pathways toward audio streaming |
| Balanced | Small absolute rank gap | Similar relative position across measured platforms | Coordinate maintenance and monitor changes |
| Portfolio breadth | Multiple tracks by one artist in high-ranking baseline | Attention distributed across more than one track | Develop cross-catalogue navigation and later test persistence |
| Social-discovery case | High TikTok sound activity with different streaming ranks | Possible divergence between discovery and consumption | Track subsequent weeks before claiming conversion |

*Source: author synthesis. The categories are exploratory diagnostics and are not validated causal segments.*

## 4. Conclusion

This study provides preliminary cross-platform evidence on the digital visibility of Indonesian musicians using a synchronized one-week snapshot. The revised sampling description treats the Spotify baseline as 30 track entries because repeated artists are present in the retained chart data. Among 11 tracks matched across Spotify and YouTube, rank positions are positively associated and weekly stream volumes show a strong positive relationship. Confidence intervals and sensitivity checks indicate that the direction of the volume association is stable, while the small sample leaves meaningful uncertainty around the exact magnitude.

The study also shows why platform association should be read together with track-level divergence. The signed rank-gap diagnostic identifies whether a matched track holds a relatively stronger position on Spotify or YouTube. Large sample-relative gaps for tracks such as "MMG", "Jatuh Suka", and "Kangen" indicate uneven concentration of visibility even when the overall cross-platform relationship is positive. Multi-track presence by Tulus and Raim Laode is retained as a descriptive indicator of portfolio breadth, not evidence of long-term catalogue persistence.

The managerial contribution is a cautious cross-platform visibility framework that separates social discovery, search attention, audiovisual visibility, audio consumption, and portfolio breadth. The framework can guide weekly diagnosis, yet it does not establish audience conversion or a fixed discovery-to-retention funnel. TikTok is used only as an illustrative auxiliary case, and Google Trends remains a future search-attention component. A composite Digital Music Visibility Index therefore remains an agenda for validation rather than an output of the present study.

Future research should use a larger fixed panel, repeated weekly measurement, normalized rank positions, archived source files, explicit rules for classifying Indonesian acts, and harmonized Google Trends queries. Lagged or panel-data models could then test whether discovery on one platform precedes consumption or broader repertoire visibility on another. With those extensions, cross-platform visibility could become a stronger evidence base for artist management while preserving the distinct meaning of each platform metric.

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## Conflict of Interest

The author declares no conflict of interest related to the publication of this article.

## References

Arenal, A., Aguado, J. M., Armuña, C., Ramos, S., & Feijoo, C. (2026). Artificial intelligence in the music streaming value chain: Exploring artists' and users' perceptions on content creation and algorithmic consumption. Telecommunications Policy, 50(2), 103129. https://doi.org/10.1016/j.telpol.2025.103129

Arrieta, A. (2025). The limits of virality: Music creators and platform negotiation in the era of short-form video. Social Media + Society, 11(4). https://doi.org/10.1177/20563051251388000

Bonini, T., & Gandini, A. (2019). "First week is editorial, second week is algorithmic": Platform gatekeepers and the platformization of music curation. Social Media + Society, 5(4). https://doi.org/10.1177/2056305119880006

Chartex. (2026). Top TikTok sounds: Indonesia. Retrieved September 2, 2026, from https://chartex.com/tiktok/sounds/24-hours/indonesia

Cheng, M. M., Ofek, E., & Yoganarasimhan, H. (2026). The value of silence: The effect of UMG's licensing dispute with TikTok on music demand. Marketing Science, 45(3), 493-514. https://doi.org/10.1287/mksc.2024.1170

Ismail, R. S., & Silooy, M. (2026). Marketing strategies of independent musicians on TikTok to introduce their works and enhance personal branding. Jurnal Manajemen dan Profesional, 7(1), 118-124. https://doi.org/10.32815/jpro.v7i1.2956

Kworb. (2026a). Spotify weekly chart: Indonesia, 2026/08/27. https://www.kworb.net/spotify/country/id_weekly.html

Kworb. (2026b). YouTube weekly chart: Indonesia, week ending 2026/08/27. https://kworb.net/youtube/insights/id.html

Ministry of Creative Economy of the Republic of Indonesia. (2026, June 25). Minister of Creative Economy applauds efforts to protect and commercialize Indonesian musicians' works through legal streaming platforms. https://ekraf.go.id/news-en/minister-of-creative-economy-applauds-efforts-to-protect-and-commercialize-indonesian-musicians-works-through-legal

Ng, J., & Gamble, S. (2026). Hip-hop music producers' labour in the digital music economy: Self-promotion, social media and platform gatekeeping. New Media & Society, 28(2), 530-548. https://doi.org/10.1177/14614448241295304

Nieborg, D. B., & Poell, T. (2018). The platformization of cultural production: Theorizing the contingent cultural commodity. New Media & Society, 20(11), 4275-4292. https://doi.org/10.1177/1461444818769694

Pachali, M. J., & Datta, H. (2025). What drives demand for playlists on Spotify? Marketing Science, 44(1), 54-64. https://doi.org/10.1287/mksc.2022.0273

Prey, R., & Lee, S. (2025). A global approach to studying platforms and cultural production. International Journal of Cultural Studies, 28(1), 30-38. https://doi.org/10.1177/13678779241244399

Rackowitz, L., & Haampland, O. (2025). The sound of salience: How platform design impacts consumption. Information Economics and Policy, 71, 101144. https://doi.org/10.1016/j.infoecopol.2025.101144

Resmadi, I. (2024). The impact of platformization on streaming music governance in Indonesia and the resistance by local indie musicians. Jurnal Sosioteknologi, 23(3), 358-373. https://doi.org/10.5614/sostek.itbj.2024.23.3.5

Sepehr, S., & Maulidina, A. (2026). Digital capitalism, platformization and coloniality: An investigation of Jakarta's positioning as a "trigger city" in the global music market. Consumption Markets & Culture. Advance online publication. https://doi.org/10.1080/10253866.2026.2646899

Shim, H., & Kim, D. (2026). Beyond the top hits: How generative AI recommendations reshape consumer choice in music streaming services. Journal of Retailing and Consumer Services, 92, 104806. https://doi.org/10.1016/j.jretconser.2026.104806

Siles, I., Valerio-Alfaro, L., & Arriagada, A. (2024). "Music is just right there on social media!": Discovering, exploring, and incorporating songs across platforms. International Journal of Communication, 18.

Spotify. (2026). Understanding Spotify charts. https://support.spotify.com/artists/article/understanding-spotify-charts/

Ta, N., Jiao, F., Lin, C., & Shen, C. (2026). A computational analysis of the platformization of music: Comparing hit songs on TikTok and Spotify. Information, Communication & Society, 29(3), 1041-1059. https://doi.org/10.1080/1369118X.2025.2539297