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Temporal Success Analyses in Music Collaboration Networks: Brazilian and Global Scenarios

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Resumo: A colaboração faz parte da indústria da música e aumentou nas últimas décadas; mas pouco sabemos sobre seus efeitos no sucesso e na evolução. Nosso objetivo é analisar como o sucesso evoluiu nas redes de colaboração e comparar seu cenário global com um cenário local próspero: a indústria fonográfica brasileira. Especificamente, construímos redes de colaboração a partir de dados coletados das paradas diárias globais e brasileiras do Spotify, analisamos e identificamos perfis de colaboração nessas redes. As análises sobre suas características topológicas revelam padrões de colaboração mapeados em quatro diferentes perfis: *Padrão*, *Nicho*, *Efêmero* e *Ausente*, onde os dois primeiros têm maior nível de sucesso. Além disso, nos aprofundamos avaliando a evolução temporal de tais perfis por meio de estudos de caso: *pop* e *k-pop* globalmente, e *BR-pop* e *forró* no Brasil. No geral, nossos resultados enfatizam a importância dos perfis de colaboração na avaliação do sucesso e mostram diferenças entre os cenários global e brasileiro.

Palavras-chave: Sucesso musical, Perfis de colaboração, Análise de redes sociais

Abstract: Collaboration is a part of the music industry and has increased over recent decades; but little do we know about its effects on success and evolution. Our goal is to analyze how success has evolved over collaboration networks and compare its global scenario to a local, thriving one: the Brazilian music industry. Specifically, we build collaboration networks from data collected from Spotify's Global and Brazilian daily charts, analyze them and identify collaboration profiles in such networks. Analyses over their topological characteristics reveal collaboration patterns mapped into four different profiles: *Standard*, *Niche*, *Ephemeral* and *Absent*, where the two first have a higher level of success. Furthermore, we do deeper by evaluating the temporal evolution of such profiles through case studies: *pop* and *K-pop* globally, and *BR-pop* and *forró* in Brazil. Overall, our findings emphasize the importance of collaboration profiles in assessing success and show differences between the global and Brazilian scenarios.

Keywords: Musical success, Collaboration profiles, Social Network Analysis.

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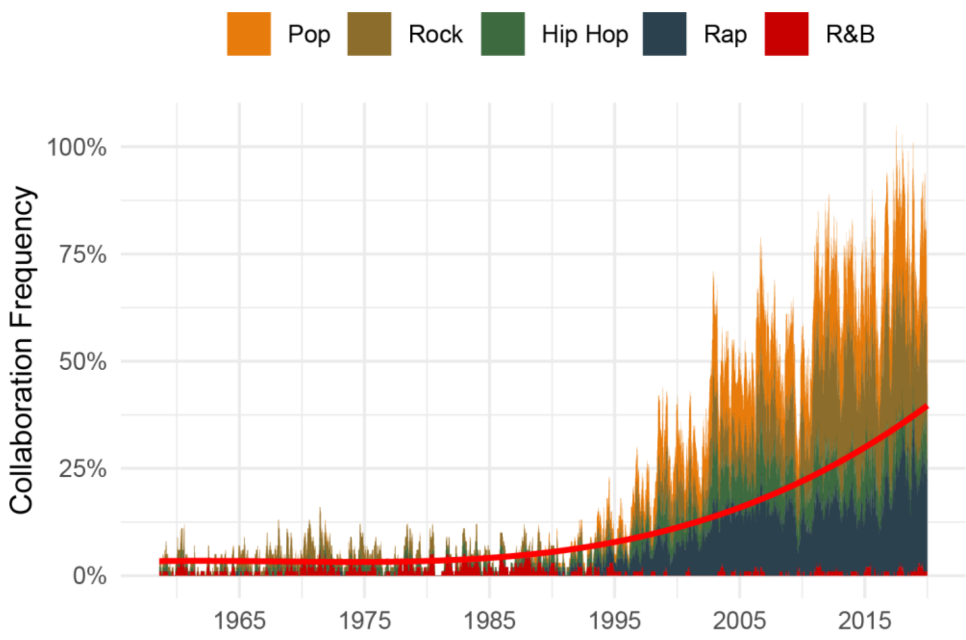
There has been a significant shift in the way people consume music, moving from physical discs to streaming services. This changing landscape directly influences the careers of artists, prompting them and their labels to devise strategies to maintain market presence and expand their audience. Collaboration between artists has emerged as a key tactic for promoting new music and reaching wider audiences, as evidenced by data from the Billboard Hot 100 (Figure 1, trend line). By the end of 2019, collaborations already accounted for over 40% of hits.

FIGURE 1 – Frequency of overall collaboration (trend line) and for main genres on the Billboard Hot 100 (1958--2020)



Source: Adapted from OLIVEIRA *et al*. (2020, p. 11)

Within the scope of this research, collaboration refers to the intentional and structured partnerships between artists in the creation and release of musical works. It entails the joint effort of multiple artists, combining their talents, creative inputs, and resources to produce collaborative music projects. Such collaborations often involve joint songwriting, vocal performances, instrumental contributions, and promotional activities. While collaborations facilitate the blending of styles and genres, they also advance to the growth of fan bases and sales numbers. Indeed, Figure 1 shows such a phenomenon and highlights the increasing trend in the number of collaborations within the Hot 100 by genre. Although the overall numbers escalate over time, genres such as *rap* and *hip-hop* have a higher collaboration rate than others (e.g., *rock* and *R&B*). This contrast can be explained by the intrinsic nature of each musical genre, where *rap* and *hip-hop* artists often engage in collaborations, particularly as featured artists, with the *pop* community.

As the industry evolves, predictive and diagnostic analytics becomes increasingly challenging, as the factors that lead to success are still not completely investigated. Therefore, it is essential to understand how collaboration profiles can positively impact the popularity of an artist or musical genres. Previous research on music collaboration networks has established that social interaction can influence the trajectory of the music industry (UZZI; SPIRO, 2005; CALEFATO; IAFFALDANO; LANUBILE, 2018; SILVA; ROCHA; MORO, 2019; OLIVEIRA *et al*., 2020). Furthermore, the influence of a specific role depends not only on the number of relationships but also on the importance of such connections.

Against this backdrop, the primary objective of this work is to analyze the success, defined in Section 2, and evolution of collaborations within the music industry, specifically examining their impact on mainstream releases. Our study leverages data collected from Spotify's daily charts (Section 3) to construct collaboration networks for artists and music genres (Section 4). Using network topological metrics, we identify distinct collaboration profiles (Section 5) and correlate these profiles with a success metric (i.e., number of *streams*) to understand the impact on popularity. It is important to note that our analysis primarily focuses on the outcome and commercial aspects of collaborations, rather than delving extensively into the intricate creative processes involved. While the creative aspects of collaborations hold significant value, our research goes deeper into understanding the impact of collaborations over success and popularity of artists and musical genres from a commercial standpoint.

Now, besides the aforementioned technical challenges, a second issue is how to analyze the music market. While investigating global performance is important, it is equally important to recognize that regional markets exhibit unique features and behaviors regarding success (PICHL *et al*., 2017; SCHEDL *et al*., 2017b; OLIVEIRA *et al*., 2020). Therefore, our analyses compare the global market with the Brazilian market. Besides being a country of continental proportions, Brazil has a rich, exquisite music scene, which has produced new, exciting musical genres such as *bossa nova*, *samba*, and *forró*. Furthermore, current research on Brazilian music has primarily focused on digital music libraries and conceptual modeling (PADRON; CRUZ; SILVA, 2018, 2020), genre classification (LIMA *et al*., 2020) and career analysis (SEUFITELLI *et al*., 2022), leaving room for us to contribute by leading collaboration analyses and global comparisons.

Overall, from topological metrics, we unveil four main factors that help to characterize the collaborative patterns detected: *Influence*, *Affinity*, *Diffusion* and *Exclusivity*. Then, our analyses results reveal four collaboration profiles presenting distinct levels of musical success: *Standard, Niche*, *Ephemeral*, and *Absent* (Section 6). Finally, we present case studies to better exemplify the impact of collaborations on the rise of musical genres: *pop* and *K-pop* on the global stage, and *BR-pop* and *forró* in Brazil (Section 7). Indeed, collaboration profiles are a powerful tool for understanding musical success, as they act as class descriptors of successful partnerships.

1. Related Work

As the world becomes more interconnected, people are often in contact with their peers, thus reducing the barriers of distance and communication that once existed. Hence, content production, in general, has become increasingly collaborative. Following the famous adage "*we go hand in hand*", the impact of collaboration on the popularity of content has become a hot research topic. For example, content created in social platforms is the subject of studies that apply various techniques ranging from information diffusion (NOBRE; FERREIRA; ALMEIDA, 2022) to neural networks (SILVEIRA *et al*., 2021).

In a broader perspective, explaining or predicting the success of creative individuals through social analysis has been challenging for decades. In the 1970s, Granovetter (1973) suggested the topology of an individual's social network has an impact on personal success. In the music scenario, different studies have analyzed the impact of acoustic and social characteristics on musical success (ARAUJO et al., 2017; COSIMATO et al., 2019; KIM; OH, 2021; VOTTER et al., 2021), some of them including genre information (ABEL *et al*., 2010; SCHEDL; FERWERDA, 2017; ZANGERLE *et al*., 2019; GIENAPP; KRUCKENBERG; BURGHARDT, 2021). However, there are few studies that focus on collaboration. For example, Uzzi and Spiro (2005) found that network metrics significantly affected creativity in terms of financial and artistic success. More recently, Calefato, Iaffaldano and Lanubile (2018) analyzed the relationship between song- and author-related metrics and the probability of a song being "*overdubbed*".[1] Then, Gienapp, Kruckenberg and Burghardt (2021) studied patterns and strategies of music collaboration in Jazz and Hip Hop communities.

However, such works ignore the hypothesis that the artists' popularity may be directly related to their *collaborative patterns*. In this sense, Silva, Rocha and Moro (2019) approach collaboration as a critical success factor, using topological properties and network science techniques to detect relevant profiles in artist networks. Such a methodology is also used by Oliveira *et al*. (2020) to detect collaboration profiles across music genre networks, adding a new layer to understanding music success. The latter also differs from others because it considers data from various markets around the globe, as each country has its own dynamics. Indeed, analyzing distinct markets worldwide is fundamental, as regional characteristics play a key role in determining popular songs and artists (PICHL *et al*., 2017; SCHEDL *et al*., 2017a; OLIVEIRA *et al*., 2020).

Having each country's dynamics considered individually is new and promising in music success analysis, and so far, there is no work that jointly considers success from artists' perspectives and musical genres. Such analysis may reveal important insights into how artists from different genres come together to make a new hit song. That is the inspiration for our work as we use data from Spotify about global and one country market (Brazil) to analyze the intrinsic factors that build musical success.

2. A Definition of Success

In this study, the notion of "success" is a key concept that underpins our analysis of collaboration profiles and their impact on artists and musical genres. Here, we define "success rate" as the total number of music *streams* credited to artists or music genres involved in collaborations during a specific year. This metric serves as a quantifiable measure to assess and compare the relative levels of success among different collaboration profiles. By focusing on the number of *streams*, we evaluate the popularity and reach of collaborative works within the context of streaming platforms.

[1] A new song is *overdubbed* when it is mixed with an existing recording.

While our definition of success rate provides a specific metric for evaluating success, it is important to acknowledge that the concept of "success" in the music industry is multifaceted and usually embraces various dimensions. These dimensions may include audience engagement, critical reception, cultural influence, commercial success, and other relevant aspects that capture the broader impact and achievements of artists and musical genres. Still, our focus goes deeper into data available on streaming platforms, which are used around the world by artists and their audiences.

3. Methodology and Data Overview

This section briefly explains the methodology for analyzing success evolution on music collaboration networks, considering both global and Brazilian markets. The first step is acquiring the data about songs, their artists and genres, which is further explained in this section. Then, the methodology follows with: building the collaboration network of artists and genres; computing metrics over the network to identify topological collaboration structures; applying a clustering method to group similar artists and genres based on the computed metrics; performing an Exploratory Factor Analysis over the topological metrics to identify semantic factors that help to understand collaborative patterns; analyzing the collaboration profiles through the identified clusters; and choosing two genres as case studies for deeper analyses.

Streaming services have become paramount in music consumption, constituting over 62% of the music industry's revenue. This transformation occurred around 2017 when streaming services supplanted other revenue sources and reached a global market value of US$13.4 billion by the end of 2020.[2] Brazil, as the largest music market in Latin America, exhibits a similar trend, with digital media accounting for approximately 72.4% of music revenue, compared to a mere 1.4% from physical media, according to the latest report by Pró-Música, an affiliate of the International Federation of the Phonographic Industry (IFPI) in Brazil.[3]

[2] IFPI Global Music Report: https://gmr2021.ifpi.org/
[3] Pro-Música Brasil Report: https://bit.ly/ProMusica2019 (in Portuguese)

TABLE 1 – Main statistics on the amount of each element within the dataset (data collected between January 1, 2017, and September 1, 2021).

	Global	**Brazil**
Daily Charts	1,704	1,704
Songs	7,031	4,382
Artists	1,949	1,510
Genres	794	497

Source: Authors

Our dataset draws from Spotify, the world's largest audio streaming service, which contains over 406 million users in 184 countries and territories.[4] Table 1 presents the main statistics of the dataset. Spotify provides daily rankings of the top 200 songs in all its markets, as well as an aggregated global chart. The dataset encompasses global and Brazilian rankings from January 2017 to September 2021. To compile the dataset, we used Spotify API[5] to gather information regarding the hit songs, the artists featured on the charts, and their corresponding music genres (in Spotify, music genres are associated with the artists).

While we acknowledge that other streaming platforms (e.g., Apple Music, Amazon Music, YouTube Music, Deezer, Tencent Music, and Yandex Music) also play significant roles in the global music streaming market, our study primarily focuses on analyzing data sourced from Spotify. This choice is based on Spotify's dominant market presence and comprehensive availability of data. Moreover, the availability and comparability of data across different streaming platforms may vary. Still, further research may explore datasets from other platforms to provide a more comprehensive analysis of the music streaming landscape.

Additionally, it is worth noting that the term “global” requires nuanced interpretation, as certain streaming services, including Spotify, are not accessible in all regions. For instance, Spotify is not available in China and has limited accessibility in Russia. These regional variations in streaming platform availability, along with the presence of other major platforms, aid the complex dynamics of the global music streaming market. While our analysis focuses on the global market, we recognize the importance of considering regional contexts and market dynamics in interpreting our findings.

[4] Spotify Company Info: https://newsroom.spotify.com/company-info
[5] Spotify API: https://developer.spotify.com

Overall, by leveraging the dataset from Spotify, our study aims to uncover insights into the success and evolution of collaborations within the music industry, shedding light on the impact of collaborations on mainstream releases. The methodology employed allows to analyze the collaboration networks, identify topological structures, understand collaborative patterns, and assess their influence on success. The subsequent sections further detail our methodology.

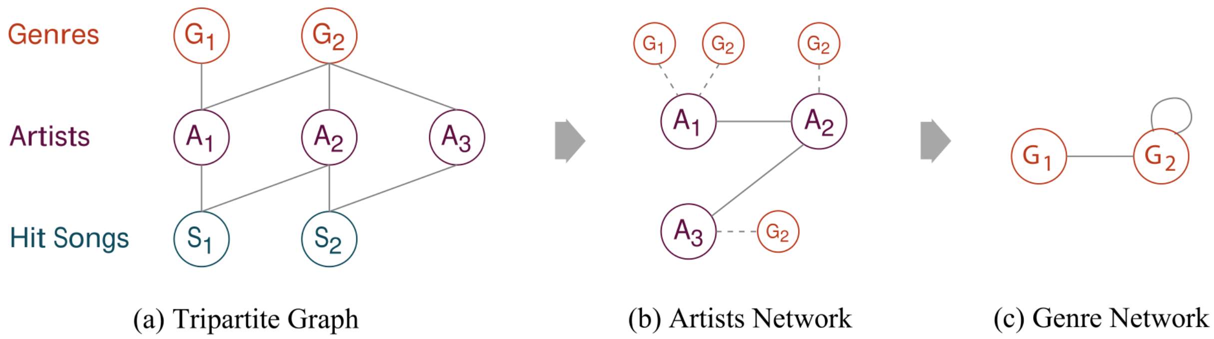
4. Collaboration Networks

After collecting success data from Spotify, we proceed to analyze collaborations between artists and music genres. This section outlines the methodology employed to construct collaboration networks of artists and musical genres (Section 4.1) and the topological metrics utilized to identify collaboration profiles (Section 4.2). By following these steps, we can gain valuable insights into the collaborative dynamics within the music industry and explore the patterns and characteristics that shape successful collaborations.

4.1. Networks Building

A collaboration network is usually modeled as a graph formed by nodes (vertices) that can be connected through edges. To analyze collaboration in the music ecosystem, we start from a tripartite graph, in which nodes are divided into three sets: genres, artists and hits (hit songs); that is, the minimum elements to assess success. Figure 2 shows the construction of the collaboration network from the tripartite model. We are interested in collaborative hits, i.e., those sung by two or more artists, regardless of their participation (for example, a typical *feat*. or a duet). In addition, we consider all genres attached to an artist equally as they shape how fans and the music industry view such an artist.

FIGURE 2 – Collaboration network building process: (a) original tripartite graph with genres, artists and hit songs; (b) network of artists with genre information; (c) reduction to musical genre collaboration network. Artists and genres are connected when hit songs engage them.



Source: Adapted from OLIVEIRA *et al*. (2020, p. 11)

From the tripartite graph (Figure 2a), a collaboration network of artists is built (Figure 2b). In such Artist Network, two artists are connected when they both collaborate on one or more hit songs. The weight of the edges is given by the number of songs that both artists perform together. Note that genres are not lost, as they are directly linked to artists. For example, Brazilian singers Anitta and Marília Mendonça are linked in the Artist Network by an edge with weight 1, since they have collaborated on one song only, *Some que ele vem atrás* (2019).

Then, we build the final network by connecting the genres of artists who collaborate in the Artist Network. The edges are undirected and weighted by the number of hit songs involving artists of both genres (Figure 2c). In addition, there may be edges of *self-loop*, as artists of the same musical genre perform songs. Going back to the previous example, the existing edge between Anitta and Marília Mendonça creates connections between the musical genres of both artists: *carioca funk*, *funk pop*, *pagode baiano*, *national pop* (Anitta); and *sertanejo*, *sertanejo pop* (Marília Mendonça). In this case, each genre of the former has edges of weight 1 (i.e., referring to the song *Some que ele vem atrás*) for all genres of the latter.

4.2. Topological Metrics

To detect collaboration profiles in both Artist and Genre Networks, we consider traditional node-related metrics from *network science*, as follows.[6]

Weighted Degree (WD). The degree of a node is the number of edges incident to it, and the weighted degree is similarly defined by the sum of the weights of such edges. The weighted degree measures the number of songs shared by a node with other nodes.

Clustering Coefficient (CC). It captures the degree to which the neighbors of a given node connect to each other. That is, the more interconnected the neighborhood of a node *i*, the higher the clustering coefficient CC_i.

Closeness (C). It corresponds to the average of the shortest paths between a node and all others in the graph. That is, high values of *closeness* indicate that all other nodes are close to the node in question, and vice versa.

Eccentricity (E). It is the maximum distance (among the shortest paths) from a node to all others in the network. If the eccentricity of a node is high, at least one node (and all its neighbors) is far from it, and vice versa.

Betweenness (B). It measures how many times a given node appears in the shortest path of other nodes in the graph. Thus, a high value indicates that a node has the potential to be highly influential in the network.

5. Cluster and Factor Analyses

This section details the approach to discovering significant factors that make up successful

[6] For more details and formal definitions, see (NEWMAN, 2010).

musical collaboration. The inspiration comes from (SILVA; ROCHA; MORO, 2019; OLIVEIRA *et al*., 2020); but such previous works consider either artist or genre collaboration, whereas we now analyze **both** dimensions simultaneously. Also, having daily charts (instead of weekly ones, as previously done) provides a more reliable success analysis. Using the five topological metrics described in Section 4.2, we perform a cluster analysis to identify collaboration profiles (Section 5.1) and then perform an Exploratory Factor Analysis to group such metrics into semantic factors to better understand the collaborative patterns (Section 5.2).

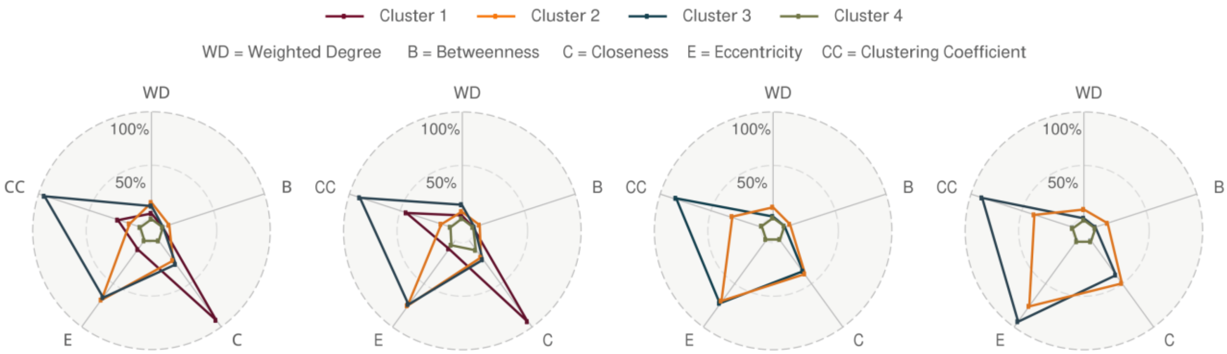
5.1. Fuzzy Clustering

Cluster analysis aims to group connections of similar artists and music genres based on the five topological metrics (Section 4.2). Unlike the methodologies followed by (SILVA; ROCHA; MORO, 2019; OLIVEIRA *et al*., 2020), here, we use *fuzzy clustering* (instead of hard clustering), as each data point may belong to more than one cluster. One of the most widely used fuzzy clustering methods is the Fuzzy C-means clustering (FCM) algorithm (BEZDEK, 1981), which assigns to each data point a probability of belonging to a specific group. This degree of relevance is determined through the proximity of the centers of the clusters.

One of the first steps when using FCM is to define the number of clusters to work with. To do so, we use the Elbow method (XU; TIAN, 2015) to identify the optimal number of clusters. Four distinct clusters were detected for most Artist Networks -- except for the 2018 global network, whose analysis resulted in three clusters. Regarding Genre Networks, only three clusters were detected in all of them, as discussed next.

To better understand the clusters, we now average the values of the normalized metrics grouped by each cluster identifier for each network, year and market. Then, we plot radar charts with the average values of the topological metrics. Figures 3a, 3b and 3c, 3d show such charts for global and Brazilian networks of artists and genres, in the year 2021, respectively, where each cluster is represented by a polygon that displays its identity. We do not present the results of previous years due to space limitations. In addition, to compare the magnitude of the metric values of each cluster, we adopt the following scale: **low**, less than 50%; **high**, equal to or greater than 50%.

FIGURE 3 – Clusters identified for the global and Brazilian networks of (a,b) artists and (b,c) genres, in the year 2021, respectively. The lines indicate the average values of the grouped topological metrics.



(a) Artists - Global, 2021 (b) Artists - Brazil, 2021 (c) Genres - Global, 2021 (d) Genres - Brazil, 2021

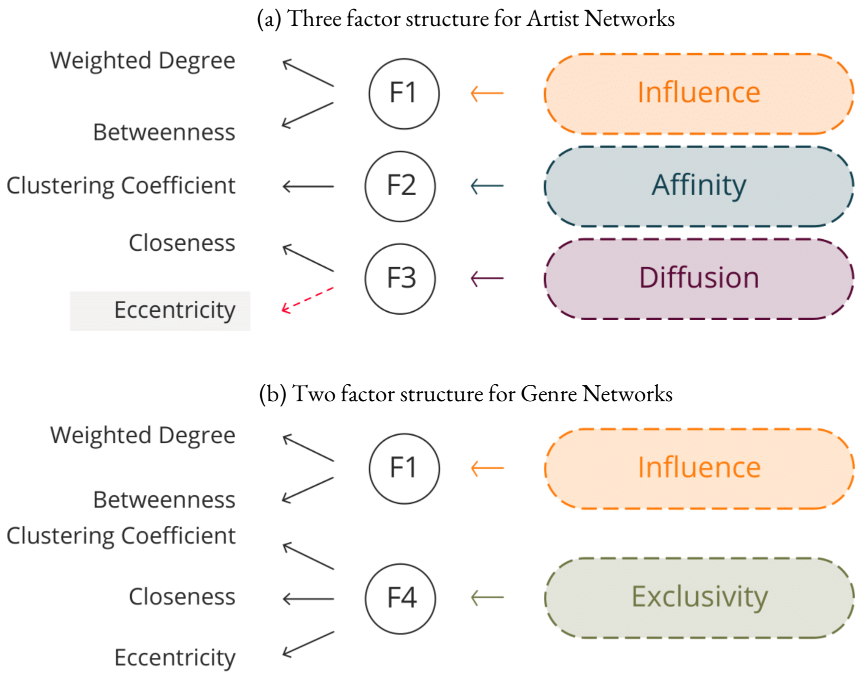
Source: Authors

The distinct polygons show that each cluster has **high** or **low** values in specific resources. For collaboration networks between artists, Cluster 1 presents artists with **high** values only of closeness, with **low** values of the other four metrics. On the other hand, Cluster 2 presents **low** values for all metrics but eccentricity. With a similar shape, Cluster 3 has **low** values of weighted degree, betweenness, and closeness but has **high** values of eccentricity and clustering coefficient. Finally, Cluster 4 has zero values for all topological metrics. These last three clusters (i.e., Clusters 2, 3, and 4) are also present in all Genre Networks.

5.2. Exploratory Factor Analysis

Exploratory Factor Analysis, or EFA (COSTELLO; OSBORNE, 2005), is a statistical method developed to underline patterns of correlations between observed variables and extract latent factors. In other words, its goal is to identify the number and nature of latent variables (factors) that best represent a set of observed variables. There are two main issues when performing EFA: determining the number of factors to retain for analysis and selecting the final structure of how the measured variables relate to the factors. As in (OLIVEIRA *et al.*, 2020), the former is solved by using the criteria of Parallel Analysis (HUMPREYS; MONTANELLI JR, 1975), based on simulation of random data. The suggested number of factors to extract is then based on the *scree plot* (CATTEL, 1966) of the observed data, which maps the factors to their eigenvalues and a cut-off point is determined whenever there is a sudden change in the slope of the line. Finally, for structure, EFA uses the Ordinary Least Squares (OLS) factoring method and an oblique rotation, allowing the factors to correlate with each other.

FIGURE 4 – EFA diagrams. Solid and dashed lines represent positive and negative correlations, respectively.



Source: Authors

We used the EFA to identify the common factors and relationships between the five topological metrics across all music collaboration networks. Such factors assist in uncovering salient dimensions of collaborations, helping to assign semantic meaning to the considered metrics and, consequently, interpreting the resulting clusters. Based on the five metrics, the analysis results suggest a three-factor structure for collaborative networks between artists and a two-factor structure for networks based on genres, regardless of market (i.e., global or Brazilian) and year. The graphical representation of both emergent structures is shown in Figures 4a and 4b, respectively. Note that Factor 1 is present in both collaboration network categories. Next, we coin names and describe each of the four factors extracted.

Influence (F1). Factor 1 has high loads for metrics weighted degree and betweenness, with a positive correlation. A node of high betweenness centrality controls a more significant fraction of the flow that passes through the network, representing a connector between two ``social circles''. The weighted degree is based on the number of edges of a node, weighted by the number of collaborations. For music, artists/genres with high values of intermediation and high values of weighted degree can be seen as social mediators who exert an influential role within the network.

Affinity (F2). Factor 2 has high loads for clustering coefficient. This factor measures the frequency of collaboration between two nodes and the social strength. It then represents artists who have a solid spectrum of collaboration in the musical context, with frequent partnerships.

Diffusion (F3). Factor 3 has high loads for closeness and eccentricity, with a negative correlation for the latter. Both metrics indicate how easily a node is accessible by all other nodes in the network. Thus, a node with high eccentricity and low proximity will be more easily influenced by the activity of other nodes. Overall, in the musical context, this factor indicates the diffusion power of artists.

Exclusivity (F4). Factor 4 has high loads for metrics clustering coefficient, closeness and eccentricity, with positive correlation. High values of such metrics indicate less accessible nodes that generally form more restricted subgraphs. In the musical context, this factor represents genres that are part of exclusive collaborative groups.

6. Collaboration Profiles

After identifying the clusters and extracting the semantic factors from the topological metrics, we summarize the characteristics of the identified clusters. Each cluster, represented by a polygon in the radar plots, serves as a collaboration profile, acting as a class descriptor for a group of artists/genres. In this section, we provide the names for each profile and describe their general statistics in Table 2.

TABLE 2 – Main statistics from collaboration profiles.

	Global						**Brazil**					
	2017			**2021**			**2017**			**2021**		
	A	**G**	**C**	**A**	**G**	**C**	**A**	**G**	**C**	**A**	**G**	**C**
Ephemeral	30		.36	54		.37	5		.35	49		.36
Standard	48	67	.51	07	13	.36	01	32	.41	64	06	.26
Niche	30	5	.00	53	11	.44	3	4	.45	71	3	.04
Absent	82	0	.00	63	8	.01	2	2	.01	0	3	.29

NA: number of artists **NG:** number of genres **AC:** average artist collaborations

Source: Authors

Profile 1: *Ephemeral.* This profile consists of artists with a high diffusion factor (**high** closeness and **low** eccentricity), making them easily accessible to all network artists. However, they exhibit low network influence and do not typically belong to closed collaboration groups (**low** weighted degree and **low** betweenness). Artists in this profile engage in fewer collaborations on average (Table 1), reflecting a less interconnected pattern of collaborations. This is the only profile that does not appear on Genre Networks, suggesting a deviation from genre-specific collaboration patterns. Examples of artists with this profile include Emicida (Brazil, 2020) and P!nk (Global, 2020). **Discussion:** The *Ephemeral* profile raises questions about the factors supporting its characteristics. One possible explanation is the nature of certain artists' creative processes, which may prioritize individual artistic expression and independence. These artists may choose to collaborate selectively or focus more on their solo endeavors. Additionally, the *Ephemeral* profile invites us to critically evaluate the broader socio-cultural and industry dynamics that shape collaborations. Factors such as artistic agency, creative preferences, and personal vision can influence an artist's decision to engage in fewer collaborations.

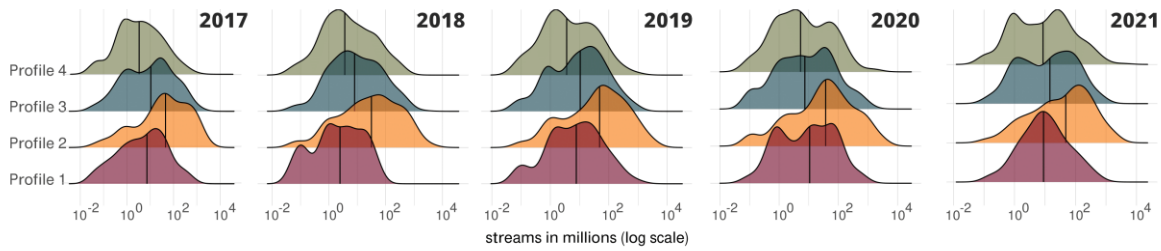
Profile 2: *Standard.* This profile encompasses most artists and genres in both markets (Table 2), indicating a prevalent pattern of collaborations. Artists within this profile have the highest average number of collaborations, but they possess low network influence (**low** weighted degree and **low** betweenness) and affinity (**low** clustering coefficient). The Standard profile serves as a reflection of collaborations that align with mainstream trends and market demands. It has most artists and genres in both markets. Examples are Anitta (Brazil, 2020) and Beyoncé (Global, 2020). These artists have engaged in numerous collaborations with various musicians, resulting in increased commercial success and exposure. **Discussion:** The *Standard* profile reflects collaborations that align with mainstream trends and market demands, often driven by factors such as audience appeal, commercial viability, and industry dynamics. However, we should still evaluate possible motivations and power dynamics that drive its collaborations. While collaborations can enhance an artist's visibility and commercial success, they can also be influenced by industry pressures, marketing strategies, and commercial interests. Exploring this profile prompts us to consider the complex interplay between artistic expression, commercial considerations, and the broader socio-cultural context in shaping collaborative endeavors. It raises questions about the balance between artistic autonomy and the market-driven nature of the music industry, emphasizing the importance of keeping a critical perspective on collaborations and their impact on the music landscape.

Profile 3: *Niche.* This profile shares similarities with the *Standard* profile, encompassing artists and genres that engage in collaborations. However, what distinguishes the *Niche* profile is its focus on forming exclusive collaboration groups within specific niches. Artists within this profile participate in collaborations that cater to niche markets and audiences, targeting specific subcultures and music scenes. Examples include Olodum (Brazil, 2020) and David Guetta (Global, 2020). **Discussion:** The *Niche* profile draws attention to the diverse subcultures and music scenes that exist within the broader music industry. Collaborations may not necessarily align with mainstream trends or appeal to a mass audience, but they play a crucial role in nurturing niche genres and cultivating dedicated fan bases. Exploring the *Niche* profile prompts us to acknowledge the social and cultural dynamics that shape collaborations, emphasizing the significance of localized and subcultural contexts in music production and success.

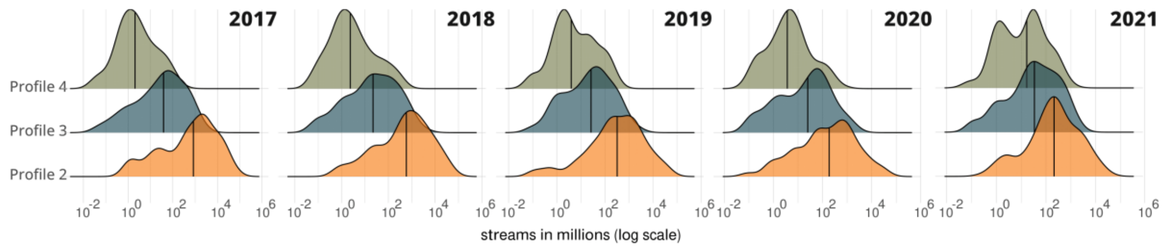
Profile 4: Absent. This profile consists of artists and genres that, in general, do not engage in collaborations. Examples include Lulu Santos (Brazil, 2020) and Adele (Global, 2020). **Discussion:** The *Absent* profile challenges the notion that collaborations are a prerequisite for success in the music industry. Artists within this profile have achieved remarkable success and recognition through their individual artistic endeavors, despite their limited involvement in collaborations. Adele's position within the collaboration networks is particularly noteworthy, as she maintains her prominence in global music without extensively participating in collaborations. Her success highlights the multifaceted nature of the music industry, where exceptional vocal abilities, emotional songwriting, distinct musical style, and powerful stage presence can transcend the traditional reliance on collaborations.

FIGURE 5 – Density estimates of total streams in millions (log scale) stratified by profile. Vertical lines represent median values.

(a) Musical success of artists



(b) Musical success of genres



Source: Authors

To better understand the relationship between collaboration profiles and musical success, we analyze the distributions of success rates for both artists and musical genres, as shown in Figures 5a and 5b, respectively. Here, we define success rate as the total number of *streams* for songs assigned to the artists or musical genres involved in collaborations during a specific year. This definition allows to quantify and compare the relative success levels of different collaboration profiles. The overall findings indicate that, on average, the *Standard* profile consists of the most successful artists and musical genres, followed by the *Niche* profile. Conversely, the *Ephemeral* and *Absent* profiles tend to have lower average success rates.

However, it is important to note that there are notable outliers within each profile, challenging the general trends. One notable example is Adele, who is among the most popular artists on Spotify but exhibits an *Absent* collaboration profile due to her tendency to refrain from collaborations with other artists.[7] Adele's success can be justified by various factors beyond collaboration, such as her exceptional vocal abilities, emotional songwriting, distinct musical style, and powerful stage presence. Her decision to refrain from engaging in collaborations with other artists may stem from her artistic vision and desire to maintain creative control over her music. Adele's success highlights the multifaceted nature of musical achievement and the diverse paths that artists can take to reach prominence.

Overall, our findings underscore the complexities and nuances of the music industry, showing success cannot be solely credited to collaborations alone. While collaborations can enhance an artist's visibility and commercial success, they are not the sole determining factor. Factors such as individual talent, unique artistic expression, and audience reception play pivotal roles in shaping an artist's trajectory. By recognizing the exceptional case of Adele and exploring the diverse range of artists within each collaboration profile, we gain a deeper understanding of the interplay between collaborations and success in the music industry.

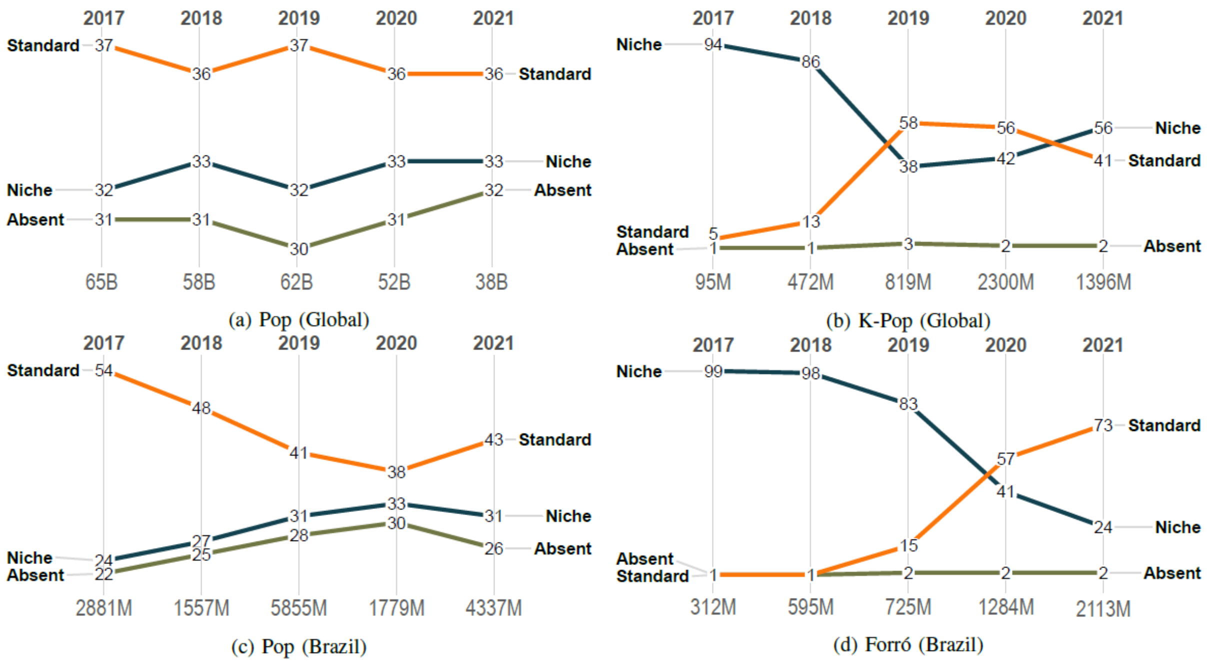
7. Case Studies

To deepen the understanding of the relationship between collaboration and musical success, we present two case studies in the global (Section 7.1) and Brazilian (Section 7.2) markets, which compare the evolution of collaboration profiles and total *streams* over time. For this, we selected the *pop*, which is already a well-established genre in both markets, as well as musical genres whose popularity has grown considerably in recent years: *forró* in Brazil and *K-pop* in the global market. We chose genres for this analysis because they are an aggregate of the artists who compose them. Thus, we were able to explain the temporal evolution of these musical styles and better understand their dynamics.

[7] Adele opens up about collaborations on upcoming new album: https://www.independent.co.uk/arts-entertainment/music/news/adele-new-album-collaborations-30-b1934463.html

Both case studies follow the same methodology described in Sections 3 to 6 but with a more focused perspective. The evolution of the profiles is based on the output of the fuzzy clustering algorithm (Section 5.1), which returns the probability of each instance belonging to a cluster. So, for each music genre in each market and year, we have the probability that it belongs to profile *Standard*, *Niche* or *Absent*. This probability can be understood as the certainty or intensity with which the genre has such a profile. Next, for each case study, we use Figure 6 to visualize each collaboration profile's annual evolution, indicating the membership percentage (y-axis) and the total number of streams in millions (bottom).

FIGURE 6 – Annual evolution of the collaboration profiles of the Global (a,b) and Brazilian (c,d) case studies. The y-axis indicates the degree of relevance (%) in each identified profile, obtained by the Fuzzy C-means algorithm. For each year, the total number of *streams* in millions is also shown in the bottom. Note the differences in the y-axis scale in each sub-figure.



Source: Authors

7.1. Pop and K-Pop within Global Market

Pop. The term "Pop" is short for popular music and was first coined in the fifties. In our analysis, "pop" refers to global pop music, which involves popular songs from various subgenres (e.g., *pop rock*, *dance-pop*, *electropop*) produced in different languages and regions, including Italian, French, Korean, and others. Pop music possesses a broad range of musicological and social attributes that extend beyond English-speaking or North-American music. Such a composition is reflected in Figure 6a, showing that the degree of relevance is well distributed among all three profiles. That is, as *pop* is a broad musical genre, its collaboration profiles probability distribution is also quite heterogeneous. Nevertheless, in recent decades, pop music has been at the top of the charts and presented a significant collaborative nature. For example, the song *(I've Had) The Time of My Life* by Bill Medley and Jennifer Warnes achieved the #1 position on charts worldwide and won several awards in 1987 and 1988, including an Oscar, a Golden Globe, and a Grammy. We still observed such behavior during our data collection period, as the pop genre remained in the Standard collaboration profile in all years (Figure 6a).

K-Pop. *K-pop* shares many similarities with pop music in terms of musicological and social attributes. However, it has unique characteristics and influences that are specific to the South Korean music industry and its cultural context. The rise of *K-pop* in the global market in recent years can be better understood with Figure 6b. The South Korean genre saw its popularity reach new heights starting in 2018 when artists like BTS and BLACKPINK started appearing on the world's top hit charts.[8] This transition is reflected by the shift in collaboration profiles, with the genre moving from the *Niche* profile to *Standard* in 2019 and 2020. *K-pop*'s success can be justified by various factors, including its origins in South Korea, the use of the Korean language (alongside English), and its distinct stylistic and cultural features. These elements have influenced its widespread popularity and fan base around the world. The significant increase in the number of *streams* received by K-pop artists, multiplying more than 24 times between 2017 and 2021, further underscores its global

[8] How K-pop became a global phenomenon: https://www.vox.com/culture/2018/2/16/16915672/what-is-kpop-history-explained

impact. In 2021, the fact that the *Niche* profile has returned to being the main one did not mean that the genre has lost popularity. As the data collection does not include the months of September to December, important releases were left out of the analysis, including the tracks *My Universe* (Coldplay feat. BTS), *Money* (Lisa of BLACKPINK) and *The Feels* (TWICE).

7.2. BR-Pop and Forró within Brazilian Market

BR-Pop. In the Brazilian context, "pop" is formed by a range of styles and genres, including MPB (Música Popular Brasileira) and Brazilian-produced pop music. Brazilian pop music merges elements from the global pop scene while incorporating regional genres such as *funk* and *sertanejo*, resulting in a unique musical identity. Artists such as Anitta, Ludmilla, and Pabllo Vittar have achieved significant national and international success,[9] then supporting the enduring popularity of *BR-pop* among listeners. Figure 6c showcases the collaboration profiles for *BR-pop*, revealing a more balanced distribution of profile characteristics over time. In 2017, although *BR-pop* was more collaborative, i.e., with a probability of 54% of belonging to the *Standard* profile, it is noted that the degree of relevance of such profile dropped considerably until 2020, similar to the pattern observed in the global scenario, in which there is a more balanced distribution of the characteristics of each profile.

Forró. Figure 6d shows the annual evolution of the genre *forró*[10] in Brazil, revealing the transition between the *Niche* and Standard profiles, starting in 2020. This major change may have been stimulated by the viralization of the musical style "pisadinha", a rhythm derived from *forró*, during the pandemic in Brazil.[11] In 2020, "pisadinha" remained high and reached the top of the most played songs on Spotify, with the song "Ele é Ele, Eu Sou Eu", by the band Barões da Pisadinha in

[9] Rio pop star Anitta becomes first Brazilian to top Spotify's global chart: https://www.nbcnews.com/news/latino/rio-pop-star-anitta-becomes-first-brazilian-top-spotifys-global-chart-rcna21625

[10] Forró refers to a musical genre, a rhythm, a dance and the event itself where forró music is played and danced and is an important part of the culture of the Northeastern Region of Brazil.

[11] Brazilian Hitmakers Play With Genre for Latin America's First Spotify Singles Series: https://newsroom.spotify.com/2022-02-03/brazilian-hitmakers-play-with-genre-for-latin-americas-first-spotify-singles-series

partnership with singer Wesley Safadão. This growth is even more evident when we analyze the annual evolution of the number of *streams* of artists in this musical genre. The number of *streams* practically tripled in 2021, when compared to 2018, when the transition between *Niche* and *Standard* started.

8. Conclusion

This article provides a comprehensive analysis of collaboration profiles in artists and musical genre networks within the global and Brazilian markets. Specifically, we built the collaboration network of artists and genres and computed commonly known network metrics to assess topological collaboration structures. Next, we grouped similar artists and genres based on the computed metrics by applying a clustering algorithm to identify collaborative patterns. Through an Exploratory Factor Analysis, we extracted semantic factors to help understand and profile the identified clusters. In particular, the structures of the networks showed four main factors that describe a musical collaboration: *Influence*, *Affinity*, *Diffusion* and *Exclusivity*.

The cluster and factor analyses unveil four different collaboration profiles: *Ephemeral*, *Standard*, *Niche* and *Absent*, which act as descriptors of artist classes and musical genres. We also analyzed the distributions of success rates for both artists and musical genres to investigate the relationship of collaboration profiles with musical success. Overall, our analysis revealed the *Standard* profile, characterized by a high number of collaborations and a broad presence in the network, tends to be associated with the most successful artists and musical genres. On the other hand, the *Ephemeral* and *Absent* profiles, characterized by limited collaborations or the absence thereof, are typically associated with lower levels of success. These findings highlight the significance of collaborations in shaping musical success, as they facilitate exposure, audience engagement, and the exploration of new creative directions.

Furthermore, we also present two case studies over *pop* and *K-pop* in the global market, as well as *BR-pop* and *forró* in the Brazilian market, providing valuable insights into the collaboration dynamics within specific genres and their impact on success. Such case studies showcased the evolution of collaboration profiles over time, emphasizing the importance of collaborative efforts in the growth and popularity of these genres. Our findings expand our understanding of the relationship between collaboration and musical success. Indeed, as shown by the case studies, detecting collaboration profiles helps to assess musical success from multiple perspectives. Overall, this work sheds light on the science behind the collaboration phenomenon, helping to better understand the music industry.

Future Work and Limitations. While this study provides valuable insights into collaboration networks and their relationship to musical success, some issues can enhance our understanding of the music industry dynamics. Firstly, expanding our analysis to include additional markets and regions is crucial for gaining a more comprehensive perspective. Each country has its own unique music industry ecosystem, cultural influences, and audience preferences, which can impact collaboration dynamics and success factors. Secondly, exploring the impact of collaborations beyond commercial success is an area worthy of investigation. While our analysis primarily focuses on success metrics such as streams and popularity, collaborations can have broader implications for artistic development, cultural impact, and audience engagement. Future studies could delve into the qualitative and quantitative assessment of these dimensions, considering factors such as critical reception, artistic growth, cultural influence, and fan engagement to provide a more holistic evaluation of collaboration outcomes.

It is also important to acknowledge some limitations of this work. Firstly, our analysis relies on data obtained from Spotify, which is one of the leading streaming platforms. While Spotify provides a comprehensive dataset, it is essential to recognize that there are other major streaming platforms, such as Apple, Amazon, YouTube Music, Deezer, Tencent, and Yandex, which may exhibit different collaboration patterns and success dynamics. Future studies should aim to incorporate data from multiple streaming platforms to provide a more comprehensive and accurate representation of the global music streaming landscape. Furthermore, the term “success” is multifaceted and can be interpreted in various ways. In this study, we focused on success as the total number of music *streams* assigned to artists or music genres involved in collaborations. While this metric provides a quantifiable measure, it is important to acknowledge that success spans over a broader range of dimensions, including audience engagement, critical reception, cultural impact, and commercial achievements. Future research could explore the integration of additional success metrics and dimensions to develop a more comprehensive framework for evaluating collaboration outcomes.

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