

Article

Information Retrieval Technologies and Big Data Analytics to Analyze Product Innovation in the Music Industry

Michele Gorgoglione *, Achille Claudio Garavelli, Umberto Panniello and Angelo Natalicchio

Department of Mechanics, Mathematics and Management, Politecnico di Bari, Via Orabona 4, 70125 Bari, Italy

* Correspondence: michele.gorgoglione@poliba.it

Abstract: In Cultural and Creative Industries, innovation contributes to generating a competitive advantage thanks to the fundamental role assumed by the human creativity and the quest for novelty. In particular, the music industry stands out as one of the most successful ones, in terms of both revenue and employment. The music industry is also quickly and constantly growing, supported by the new digital technologies and the rise of streaming platforms and digital services, which have increased the availability of continuous, reliable, and timely data. Consequently, this may allow the implementation of novel techniques to study product innovation occurring in the music industry. Nonetheless, quantitative approaches to study innovation in this industry are scant. The present study aims at filling this gap by developing a quantitative approach to analyze product innovation dynamics in the music industry exploiting data collected through Music Information Retrieval technologies. We selected a successful band as a case study and analyzed each song released from 1984 to 2016 to obtain a quantitative representation of their musical production. We then developed and applied quantitative similarity metrics to see how each album was similar or different from the previous ones and from the most relevant music genres, to better understand innovation dynamics in music production.

Keywords: cultural and creative industries; music information retrieval; big data; innovation; innovation dynamics



Citation: Gorgoglione, M.; Garavelli, A.C.; Panniello, U.; Natalicchio, A. Information Retrieval Technologies and Big Data Analytics to Analyze Product Innovation in the Music Industry. *Sustainability* **2023**, *15*, 828. <https://doi.org/10.3390/su15010828>

Academic Editor: Luigi Aldieri

Received: 10 November 2022

Revised: 9 December 2022

Accepted: 29 December 2022

Published: 3 January 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Innovation is a necessary task for organizations to compete in fast moving markets, to constantly evolve, to meet their stakeholders' needs and expectations, and to survive in an ever-changing environment [1]. Developing innovative products can often make the difference in standing out against competitors in complex markets and in gaining a competitive advantage [2].

Innovation is particularly crucial in the Cultural and Creative Industries (CCI), a conglomerate of different economic activities including advertising, architecture, art, crafts, design, fashion, film, music, performing arts, publishing, R&D, software, toys and games, TV and radio, and video games [3]. In a field that is strongly dependent on the creative input of artists and authors, the quest for novelty and innovation is indeed fundamental to compete. Researchers suggest that "human creativity is the ultimate economic resource" [4], and that "the industries of the twenty-first century will depend increasingly on the generation of knowledge through creativity and innovation" [5]. These suggestions are confirmed by the increasingly relevant contribution that CCI have been giving to the worldly economic wealth: EY in 2015 estimated that CCI generated as much as \$2.25 trillion in revenue, employing nearly 30 million people worldwide, across different continents. Specifically, the Asia-Pacific area was responsible for the 34% of the worldly CCI revenues, leading the gaming industry and quickly growing in the books and movies ones; Europe was responsible for the 32% of the worldly CCI revenues, leading in the historical and heritage-based industries; North America made up for the 28% of the worldly CCI revenues, with leading and having

a strong international influence in the movies, TV, performing arts, and music industries. Moreover, in each of the aforementioned continental markets, CCI were responsible for more than the 3% of the regional Gross Domestic Product [6]. In the conglomerate of the CCI, the contribution of music is particularly relevant. In fact, music industry generates around \$65 billion through its core and complementary businesses combined, and employs almost 4 million people worldwide, a value second to visual arts only [6]. In addition, the music industry has been also recently enjoying a constant growth, which is mainly thanks to the widely adopted streaming services (worth \$13.4 billion in revenue and reporting a 19.9% growth from the previous year). As a result, the core business of the industry is generating more than \$21 billion worldwide—its biggest value ever—largely offsetting the losses reported by the decline of the revenues in the sales of physical formats and revenues from performance rights, as a result of the COVID-19 pandemic [7].

Within this context, organizations are increasingly dealing with an unprecedented availability of data that can be leveraged to provide innovative and high-value offerings to customers [8,9]. Indeed, the increasing digitalization of industries is providing organizations with the possibility to access continuous, reliable, and timely data streams [8]. Hence, on the one side, Big Data allows to better tailor organizations' offering on clients' needs, through a more accurate understanding their behavior; on the other side, Big Data analytics also may offer tools to investigate the innovative dynamics within CCI and the evolution of the features of creative and cultural products [10]. In particular, firms can leverage Big Data analytics to develop new knowledge and infer relevant information about their business processes, resulting in an increase in the management effectiveness, performance, and the consequent establishment of a competitive advantage [10,11]. However, while evidence about the use of Big Data analytics in CCI is increasingly available in the extant academic literature (e.g., [12,13]), only recently, a limited number of studies has been focusing on increasing the understanding about generalized methodologies that can be used to extract informational value from Big Data (e.g., [14–17]). This is especially true for music products, which are difficult to analyze by separating and isolating their inner fundamental elements, such as rhythm, chords progressions, dynamics, and danceability. Indeed, so far, the extraction of information about some features of a musical composition is generally made by critics. Therefore, quantitative approaches may be particularly helpful to quickly and objectively analyze the huge number of musical compositions available nowadays. Nonetheless, demonstrations of these approaches and their usefulness are, to the best of our knowledge, infrequent in the academic literature. This issue is not only methodological, but the definition of quantitative approach may also drive advancements in the innovation management literature. More specifically, Big Data could be leveraged to study the product innovation dynamics in CCI from an original and potentially pathbreaking perspective. Hence, these methodological and theoretical gaps call for the definition of quantitative techniques and processes to extract relevant and valuable information from Big Data.

In this study, we aim at answering this call by presenting an attempt to develop a quantitative approach to analyze innovation dynamics in the music industry. The approach is based on Music Information Retrieval (MIR). MIR is the interdisciplinary science of retrieving information from music, based on the extraction of musical and perceptual properties directly from the audio signal [18]. The extraction and representation of these features allow researchers to develop quantitative metrics representing the characteristics of a song or a set of songs. It is possible, for instance, to measure how different two or more songs are and how an artist innovated her/his style along her/his career. In other words, the application of these metrics to a set of songs composed by an artist in a given period of time can show the way the artist gradually strayed away from her previous productions and started experimenting with new, innovative products. The same methodology, when applied to an appropriate set of songs and period of time, can show the way artists recombine past productions in order to produce new music. Hence, in this study, we show how to adopt a quantitative technique exploiting Big Data to investigate product innovation dynamics in the music industry.

We analyzed a case study, the worldwide famous and successful rock band Red Hot Chili Peppers (RHCP). We analyzed 11 albums released by the band from 1984 to 2016. For each song in every album, we extracted 14 musical features directly from the audio signal and obtained a quantitative representation of the artistic product. We then developed and applied quantitative similarity metrics to see how each album was similar or different from the previous ones and from the most relevant music genres. This led to represent the trajectory of innovation in RHCP music.

Our findings can be summarized as follows: the analysis of data led to the highlight that it is initially possible to observe a period of experimentation of different genres. Once a variety of solutions have been explored, those are recombined in different proportions to find the optimal style for the band. Once the ideal and commercially successful solution is found, the band sticks to it and only makes slight changes in the next releases.

Our study provides methodological, theoretical, and practical contributions. We discuss a solution to leverage Big Data in the music industry to analyze the evolution of music products. By computing several indicators from widely available data, we show the main features of music albums that may affect the customers' perception of music product. Furthermore, from a theoretical perspective, our findings may be leveraged to better comprehend innovative trajectories in the music industry. Accordingly, we contribute to the product innovation literature, with a particular focus on product innovation in CCI and, more specifically, in the music industry. Finally, our findings may offer practical inspiration to managers in the music industry concerning the use of Big Data to understand and inform product innovation strategies. For instance, the proposed methodology may be leveraged to favor the establishment of collaboration among artists to exchange knowledge to innovate music products, in an open innovation fashion [19].

2. Theoretical Background

Product innovation is one of the main topics investigated in the innovation management literature since its early infancy [20]. Indeed, product innovation can be paramount to establish organizations' competitive advantage, but it is also a costly and highly risky process [21]. Accordingly, studies have been investigating product innovation to spot success factors that can increase the likelihood of developing a new product appreciated by customers [22]. Furthermore, scholars have been posing increasing interest in understanding the dynamics of evolution of new products' features, to comprehend how organizations innovate their products by focusing on the improvements of specific features (e.g., [23,24]).

Actually, previous studies pointed out that an innovative product design can be a crucial factor to increase the likelihood of market success of a new product [21,25]. More specifically, Moon et al. [21] suggested that innovative product design can be perceived by customers in relation to different dimensions, on the basis of: (i) aesthetic attributes, i.e., visual attributes as shape, color, form, and style; (ii) features attributes, i.e., functional attributes referring to components, technical value, and performance; and (iii) ergonomic attributes, i.e., attributes as comfort, safety, and efficiency related to the use of the product. By analyzing the evolution of these attributes, it is possible to investigate the innovation of products over time and its dynamics (e.g., [26]). The relevance of product evolution and its consequence on reshaping markets is evident in the analysis of disruptive innovation. In fact, disruptive innovation emerges when product innovation focuses on enhancing secondary attributes that are initially appreciated by a market niche, but eventually result in a rapid growth that spoils incumbents of their competitive advantage [27]. Furthermore, the interest of scholars towards product attributes, especially technical ones, is testified by the stream of research on technometrics, which uses the functional characteristics of the products to investigate the innovation dynamics and technological progress [26,28]. Technometrics analyses have been also pushing researchers to spot appropriate indicators, in order to study the evolution of technological trajectories and the emerging of innovations.

However, whereas Moon et al.'s [21] taxonomy can be considered as exhaustive of the dimensions of product design innovation, the various attributes may affect the choice

of customers to a different extent according to the specific industry under investigation (e.g., [29]). In this study, we focus our attention on music industry, where aesthetic and features attributes may assume higher relevance with respect to ergonomic attributes. In fact, on the one side aesthetic attributes are definitely relevant in music industry to drive the consumers' purchasing choices [30], on the other side features attributes, related to objective technical characteristics of music, are also critical to characterize a product since they can be typical of a genre and purposely selected by an artist [31]. Therefore, these features could be used to analyze how products are innovated in the music industry context and, for this reason, we focus on them in our analysis. Musical features can be split into computational features, referring to the mathematical analysis of the signal, and perceptual features, related to how humans perceive music [32]. Furthermore, computational features are grouped into dynamics and spectral features, while perceptual features are divided into rhythm and tonal features [32]. Several sets of features have been used in the extant literature to characterize music. The MIR tool Essentia provides a list of computational features that can be used to characterize music compositions (see the Methodology section for more details) [33,34]. Furthermore, recently, Spotify, the Swedish audio streaming service used by about 456 million users [35], has developed a list of music features, covering mainly perceptual features, that can be used to complement those offered by Essentia (see the Methodology section for more details) and that has been increasingly adopted in the academic literature (e.g., [36–38]). By integrating the features provided by Essentia and Spotify, we defined a framework of features that covers both computational and perceptual ones and allow to describe a music composition more comprehensively. Therefore, this framework can be applied to understand product innovation dynamics in the music industry.

Big Data in the Music Industry

The emerging opportunities due to the digitalization of music products and the related increasing availability of Big Data in this industry have enabled the development of techniques to measure music products features and extract quantitative information. For instance, Big Data offer the opportunity to test songs before they are released on the market, by collecting and analyzing the feedback of a panel of consumers [39,40], or enables new business model to support artists in increasing their revenue due to music streaming [41]. Moreover, while the use of data to inform music business has been traditionally exploited in the industry, the granularity and the timeliness of data enabled by digitalization in the music industry pave the way for developing more detailed, useful and in-depth methodologies to analyze data [42]. A typical application of this may be related to the development of recommending systems [43] or the forecasting of the potential success of music compositions [44], nonetheless Big Data may also support product innovativeness in the music industry. In fact, by analyzing the knowledge about consumers' preferences provided through data about music listened on streaming platforms, companies can trigger product innovation to develop new products targeted to specific typologies of customers, in an open innovation fashion [19].

In addition, as above mentioned, nowadays it is possible to analyze product (i.e., music composition) features by automatically extracting information thanks to the adoption of MIR technologies. The extraction and representation of music products' features allow researchers to develop quantitative metrics representing a song or a set of songs, such as an album. The application of MIR technologies is being recently facilitated by the availability of Big Data. In fact, MIR technologies may be fed with data to calculate indicators representing music product design features that could be useful to investigate how these features evolved during time and, consequently, to analyze product innovation in the music industry.

Nonetheless, despite the growing interest on the use of Big Data in the music industry, the extant literature lacks methodologies that exploit Big Data to analyze innovation dynamics. MIR-based technologies have the potential to advance our knowledge in inno-

vation studies. We aim at filling this gap by showing an application of MIR tools to analyze product innovation dynamics and concurrently better comprehend innovative trajectories in the music industry.

3. Methodology

To investigate the product innovation dynamics occurring in the music industry, we decided to rely on a tool capable of extracting quantitative information from music products, such as tracks or albums, leveraging MIR technologies. There are various MIR tools, designed and built for different purposes and levels of skill or experience; however, two general purpose ones were deemed as appropriate for the specific application of the present study. MIR is the interdisciplinary science, and a collection of techniques, that deals with Big Data and extracts useful information from music. It represents the applications of Information Retrieval to music. Data sources in MIR have often very large sizes and are unstructured. Digitalization, and the consequent deep change in the structure of music business, has made data widely available. In our research we used software tools also deployed by business applications, such as Shazam, which aim at processing this unstructured data sources in a very short time. For these reasons, MIR indeed belongs to the family of Big Data Analytics approaches.

Essentia is the first MIR software used for the extraction of features in the current analysis. It is an open-source Python library capable of retrieving quantitative musical properties from “lossless” audio signals, such as FLAC tracks or sets of tracks.

The other MIR tool is SpotiPy, another open-source Python library, which focuses on the extraction of quantitative musical and perceptual properties from tracks belonging to the Spotify catalogue and relies on the Spotify for Developers platform. While the musical features identify melodic, tonal, or rhythmic characteristics of the analyzed track, the perceptual ones refer to metrics, specifically computed based on the musical ones, which are representative of how a track is perceived by listeners and how it compares to other tracks. These metrics were computed and defined by The Echo Nest, a music intelligence platform belonging to Spotify and integrated into Spotify for Developers.

Through the combined utilization of both tools, it is possible to obtain, for each track submitted to the MIR process, the values of 14 different computational and perceptual features: each track is thus represented as a vector made of 14 components.

The features extracted using Essentia are Duration, Beats Per Minute (BPM), Integrated Loudness, Loudness Range, Average Loudness, Spectral Centroid, and Dynamic Complexity. The features extracted using SpotiPy are Beats Per Minute Confidence, Time Signature and Time Signature Confidence, Danceability, Energy, Speechiness, Acousticness, and Valence.

To develop a quantitative approach to analyze innovative dynamics in music, we selected a band that we used as a case study and considered each band’s album as the unit of analysis. The reason is that each album has a unique release date, and this allows us to set a temporal representation of the band’s production and to investigate the magnitude of change in time. Once all the tracks of an album are transformed into the corresponding vectors, we can compute the centroid of the album. The centroid is a single 14-component vector representative of one album, where each component is the mean value computed over the album songs. The set of centroids representing all the albums released by the band is a quantitative representation of all the band’s production in time.

We also represented the music genres and styles that the artists were inspired by during their career. Firstly, we identified the main inspiring genres by analyzing the major articles issued by music critics.

The SpotiPy metrics obtained through the MIR process serve as a comparative measure to highlight how, with every new album, the artist/band approached a new specific genre or strayed away from it, or how the style pursued in a specific release derives from a recombination of previous styles. The features that are deemed appropriate for the identification of genres are the following:

1. Beats Per Minute (BPM): a measure of frequency used for rhythmical references about the track. It does not stay constant throughout the length of the track, therefore a single average value is computed. Different music genres are characterized by different ranges of BPM values.
2. Energy: a perceptual measure, with values between 0 and 1, that refers to the intensity and the general motion of the track. High values are representative of quick, strong, and loud tracks, hence gradually increasing values are linked to heavier genres, such as Rock or Metal.
3. Average Loudness: a measure of the dynamic interval, with values between 0 and 1, which computes the average volume of the track. Values close to 0 are representative of a smaller dynamic interval, values close to 1 are representative of a larger dynamic interval.
4. Valence: a perceptual measure, with values between 0 and 1, of the musical positivity, catchiness, and cheerfulness transmitted by a track. Values close to 0 are indicative of tracks characterized by sadness, anger, and depression, and values close to 1 are indicative of tracks characterized by joy, happiness, and euphoria. Gradually increasing values are therefore linked to more upbeat genres, such as Electronic Dance Music (EDM), Funk, Disco, and Pop.
5. Danceability: a perceptual measure, with values between 0 and 1, that computes how “danceable” a track sounds. It is based on a combination of physical factors such as BPM, BPM stability, intensity of the beat, and general regularity. Values close to 0 are indicative of less danceable tracks, values close to 1 are indicative of more danceable tracks. Gradually increasing values are linked to genres that are considered more appropriate for dancing, such as EDM, Funk, Disco, and Pop.
6. Speechiness: a measure, with values between 0 and 1, of how close to a full speech the lyrics of a track sound. Values close to 0 are indicative of mainly “sung” lyrics, values close to 1 are indicative of mainly “spoken” lyrics. Genres such as Rap and Hip Hop tend to have higher values than others, while tracks such as audiobooks or talk shows report the highest values.
7. Acousticness: a measure, with values between 0 and 1, of the intensity of the music recorded from unplugged instruments in the track. Values close to 0 are indicative of a heavy presence of electric or electronic instruments, values close to 1 are indicative of a heavy presence of unplugged instruments. Gradually increasing values are linked to genres such as Folk and Country, or to tracks such as ballads.

The representation of these measures in time provides a picture of the artist/band’s evolution. Indeed, these indicators are applied to understand if and how a band innovates itself and the related trajectory of innovation. In other words, by looking at the indicators and how they change during time, we can have an accurate and novel perspective about how innovation unravel at a single band level.

Our long-term research goal is to prove a set of hypotheses taken from an observational study and conducting a set of experiments to build a theory based on those hypotheses. However, at this first research stage we build and test a novel approach through a case-study and followed the case-study research methodology to provide a rigorous argument.

4. Case Study

This research is based upon a single case study methodology, which was deemed as an appropriate research strategy to understand the phenomenon under investigation by relying on several sources of evidence [45–47]. Accordingly, we selected Red Hot Chili Peppers (RHCP), the famous American Alternative Rock band from Los Angeles, California. As one of the world’s most famous acts, the band looked appropriate for the study thanks to their long-running career (spanning on five decades), the huge commercial success enjoyed by their singles and albums, and the critic reception. Consequently, the availability of albums spanning decades and remarkably including 166 songs provided us with enough data to apply MIR tools without concerns on the reliability of the results.

Moreover, thanks to the huge contribution to the rise to popularity of Alternative Rock (of which RHCP represent one of the most widely known and successful band) and the incorporation of extremely diverse styles and influences that helped them forge a very unique identity, critics have often judged their music quite innovative [48]. Hence, using MIR algorithms to analyze innovation in RHCP music can provide interesting findings related to the investigation of innovation dynamics in the music industry.

As previously described in the methodology, each album that is part of the whole band's discography was processed by MIR algorithms to turn it into a 14-component vector. The albums included in the analysis are:

1. The Red Hot Chili Peppers (TRHCP): released in 1984, 11 tracks
2. Freaky Styley (FS): released in 1985, 14 tracks
3. The Uplift Mofo Party Plan (TUMPP): released in 1987, 12 tracks
4. Mother's Milk (MM): released in 1989, 13 tracks
5. Blood Sugar Sex Magik (BSSM): released in 1991, 17 tracks
6. One Hot Minute (OHM): released in 1995, 13 tracks
7. Californication: released in 1999, 15 tracks
8. By The Way (BTW): released in 2002, 16 tracks
9. Stadium Arcadium (SA): released in 2006, 28 tracks
10. I'm With You (IWY): released in 2011, 14 tracks
11. The Getaway (TG): released in 2016, 13 tracks

As described in the methodology section, each song was processed and turned into a vector. For each album we calculated the corresponding centroid. The 11 centroids are reported in Table 1.

4.1. Analysis of Album-On-Album Differences in Time

The centroids in Table 1 are a quantitative representation of the band's production in time. This allows to analyze the differences between albums by simply applying a difference metric. Since the centroids only include scale variables, we computed the Euclidean distances to spot the differences between subsequent albums. Figure 1 reports the album-on-album Euclidean distances for the whole discography.

Although with several limitations, this is a quantitative representation of the magnitude of difference the band chose to put in each album with respect to the previous. Therefore, it gives a rough depiction of how the earlier albums resulted more different, compared to the immediate predecessor, than the later albums did. This shows how the band decreased the experimentation with new kinds of music through the years and, consequently, reduced the innovativeness of new albums in comparison with the previous ones.

Table 1. Centroids of the RHCP's discography.

Centroids	Duration (Sec)	BPM	Danceability	Energy	Speechiness	Acousticness	Valence	Integrated Loudness	Loudness Range	Average Loudness	Dynamic Complexity	Spectral Centroid Mean	Spectral Centroid St. Dev.	Chords Change Rate
TRHCP (1984)	176.84	106.21	0.65	0.82	0.09	0.08	0.48	−11.51	3.79	0.84	5.28	1492.21	740.95	0.09
FS (1985)	172.12	102.92	0.62	0.83	0.07	0.16	0.64	−12.59	5.30	0.86	5.41	1530.95	733.78	0.10
TUMPP (1987)	192.10	111.34	0.61	0.92	0.13	0.02	0.36	−11.06	3.81	0.91	3.71	2091.37	755.74	0.11
MM (1989)	215.27	124.52	0.46	0.94	0.13	0.01	0.40	−16.30	3.60	0.93	3.68	1770.31	559.82	0.10
BSSM (1991)	260.91	120.85	0.58	0.75	0.06	0.01	0.63	−10.18	3.90	0.82	3.55	1645.85	741.80	0.10
OHM (1995)	283.86	113.36	0.48	0.78	0.07	0.09	0.40	−8.14	7.26	0.87	3.49	1433.81	661.32	0.08
Californication (1999)	225.93	116.59	0.46	0.83	0.10	0.06	0.46	−5.81	4.51	0.92	3.10	1743.85	931.90	0.10
BTW (2002)	257.36	122.27	0.51	0.82	0.06	0.04	0.38	−7.91	5.53	0.89	3.28	1571.07	858.34	0.06
SA (2006)	262.48	120.82	0.52	0.79	0.06	0.09	0.50	−7.57	6.94	0.79	3.89	1775.71	686.71	0.06
IWY (2011)	254.54	120.09	0.56	0.86	0.06	0.05	0.50	−5.76	4.92	0.93	3.10	1203.47	609.71	0.06
TG (2016)	248.26	119.57	0.54	0.73	0.07	0.18	0.55	−7.86	4.93	0.92	3.15	974.56	582.36	0.06

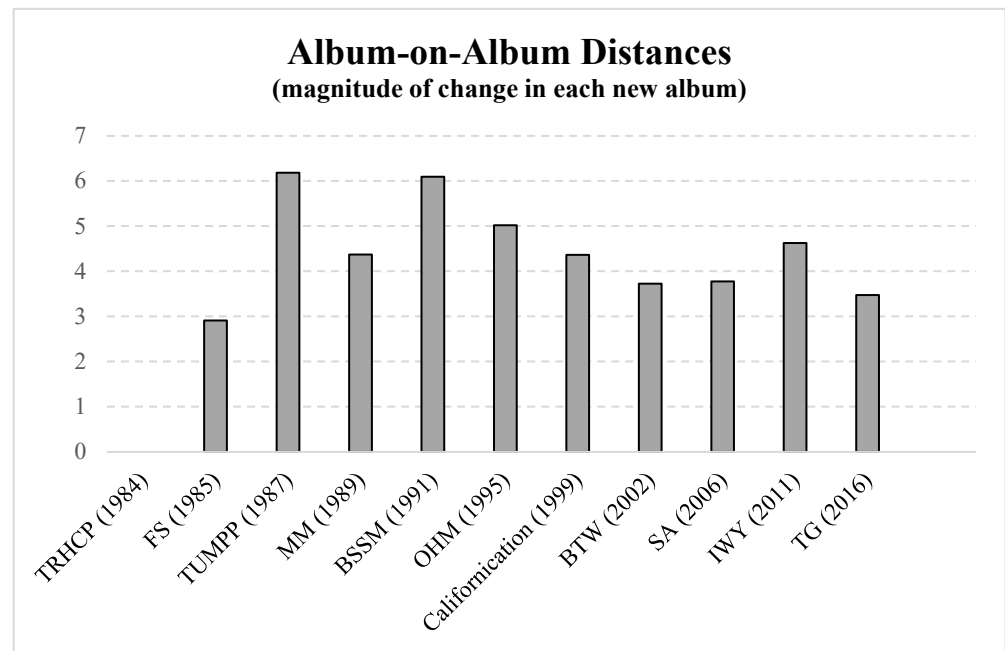


Figure 1. Album-on-album Euclidean distances.

4.2. Analysis of Search and Recombination to Innovate

We looked at relevant music critic international sources to identify the main music genres the music of RHCP was inspired by. It can be classified as Alternative Rock, Funk, Hip Hop, Pop Rock, and Psychedelic Rock, also with Metal influences in the first phase of their career. The analysis therefore focuses on the aforementioned genres to determine how the band moved across those genres and recombined them in the search of innovative products [49]. In this way, we offer a data-based perspective about the trajectory of innovation in music followed by the band.

This analysis can be carried out by looking at the seven musical features discussed in the Methodology section, namely BPM, Energy, Average loudness, Valence, Danceability, Speechiness, and Acousticness. The reason is that high or low values of these features characterize the music genres that critics have said to be inspirational for the band. Particularly, the music belonging to the genres known as Alternative Rock, Pop Rock, Psychedelic Rock, and Metal is characterized by high values of BPM, Energy, and Average loudness, while the other features are typically low. On the contrary, Pop music has typically low values of Energy and Average Loudness, while Valence and Danceability are high. Instead, Hip Hop songs generally show high value of Speechiness and Danceability, which is a feature also characterizing Funk music.

Therefore, the analysis can be performed by calculating the increases and decreases of the values of each one of the seven features from one album to the other. As an example, an increase in Energy and Average loudness, that are typically high in Rock music, means the band was making leaning towards Rock music. In other terms, the band was innovating its music by introducing elements typical of the Rock genre. An increase in Speechiness from one album to another means the band was using features typical of Hip Hop in its music. The use of features that are typical of several musical genres is a signal that a musician, or a band in this case, is recombining different genres in search of an innovative product. To perform this analysis and for the sake of clarity, we consider a reduced version of the centroids shown in Table 1, obtained by taking only the seven features mentioned above. The vectors are listed in Table 2.

Table 2. Values scored by each centroid on the genres' features.

Centroids	BPM	Energy	Average Loudness	Valence	Danceability	Speechiness	Acousticness
THRCP (1984)	106.21	0.82	0.84	0.48	0.65	0.09	0.08
FS (1985)	102.92	0.83	0.86	0.64	0.62	0.07	0.16
TUMPP (1987)	111.34	0.92	0.91	0.36	0.61	0.13	0.02
MM (1989)	124.52	0.94	0.93	0.40	0.46	0.13	0.01
BSSM (1991)	120.85	0.75	0.92	0.63	0.58	0.06	0.01
OHM (1995)	113.36	0.78	0.87	0.40	0.48	0.07	0.09
Californication (1995)	116.59	0.83	0.92	0.46	0.46	0.10	0.06
BTW (2002)	122.27	0.82	0.89	0.38	0.51	0.06	0.04
SA (2006)	120.82	0.79	0.79	0.50	0.52	0.06	0.09
IWY (2011)	120.09	0.86	0.93	0.50	0.56	0.06	0.05
TG (2016)	119.57	0.73	0.92	0.55	0.54	0.07	0.18

Starting from these vectors, we calculated the album-on-album percentage differences for each component as the difference between the values in two consecutive albums divided by the value of the first album as in the following formula (1):

$$\text{Album-on-album difference (\%)} = [(feature(t) - feature(t - 1))/feature(t - 1)] \quad (1)$$

where *feature* is each one of the seven features, *t* is the release date of an album, and *t* − 1 is the release date of the previous album. The computed metrics are reported in Table 3:

Table 3. Album-on-album percentage transition for each feature.

Centroids	BPM	Energy	Average Loudness	Valence	Danceability	Speechiness	Acousticness
1984–1985 Transition	−3%	1%	3%	33%	−5%	−22%	100%
1985–1987 Transition	8%	11%	7%	−44%	−2%	86%	−88%
1987–1989 Transition	12%	2%	2%	11%	−25%	0%	−50%
1989–1991 Transition	−3%	−20%	−1%	58%	26%	−54%	0%
1991–1995 Transition	−6%	4%	−5%	−37%	−17%	17%	800%
1995–1999 Transition	3%	6%	5%	15%	−4%	43%	−33%
1999–2002 Transition	5%	−1%	−4%	−17%	11%	−40%	−33%
2002–2006 Transition	−1%	−4%	−11%	32%	2%	0%	125%
2006–2011 Transition	−1%	9%	18%	0%	8%	0%	−44%
2011–2016 Transition	0%	−15%	0%	10%	−4%	17%	260%

By looking at these values, we can analyze how, across the years, the band innovated its music with respect to each feature and what music genres were recombined accordingly.

BPM: THRCP (1984) and FS (1985) are characterized by common BPM values of genres such as Funk and Hip Hop. With TUMPP (1987), there is an initial increase of BPM (8% higher compares to FS), furtherly accentuated with MM (1989), which has a value 12% higher than TUMPP. It is then possible to observe a slight decrease (−3% compared to MM) with BSSM (1991), which leads to a bigger one (−6% compared to BSSM) with OHM (1995)

and to a slight rise (+3% compared to OHM) with *Californication* (1999). After another slight increase (+5% compared to *Californication*), the band's output stabilizes on average values around 120 BPM in their last four albums, typical of genres such as Mainstream Alternative Rock and Pop Rock.

Energy: the starting points of TRHCP (1984) and FS (1985) lead to a relevant increase (+11% compared to FS) with TUMPP (1987), furtherly accentuated with MM (1989), the band's most energetic album, which scores Metal-like values. The Energy values then dramatically drop (−20% compared to MM) with BSSM (1991), before having a slight rise and staying on very similar levels from 1995 to 2006. IWY (2011) then scores a relevant increase (+9% compares to SA), while TG (2016) reports a significant drop (−15% compared to IWY), becoming the band's least energetic album.

Average Loudness: the starting points of TRHCP (1984) and FS (1985) score lower values than TUMPP (1987), MM (1989), and BSSM (1991), indicative of a less loud style for the former albums (Funk-oriented) and a louder style for the latter (Rock and Metal-oriented). After a noticeable decrease (−5% compared to 1991) with OHM (1995), the band then increase their loudness again with *Californication* (1999) and veers towards a slightly slower, although still generally high, value with BTW (2002). The lowest value (−11% compared to BTW) of loudness is scored by SA (2006), an album which contains a higher-than-usual number of ballads. A large increase (+20% compared to SA) is then seen with IWY (2011), with a value that roughly stays constant with TH (2016) as well.

Valence: the starting point of TRHCP (1984) is followed by a large increase (+33%) and the highest value in the band's career, marked by FS (1985). An approach oriented towards heavier and less catchy products is visible starting from TUMPP (1987), with a 44% decrease compared to FS, and stays until BTW (2002), similarly to what has been observed with Energy, with the only exception of BSSM (1991), which scores a similar value to the peak one and reports a 55% increase compared to TUMPP. In their three most recent albums, from 2006 to 2016, the band stabilizes around average values between the peak and the bottom ones, with TG (2016) scoring the highest value after the times of BSSM, indicative of a generally catchier and positive style.

Danceability: the starting points of TRHCP (1984), FS (1985), and TUMPP (1987) mark the band's highest values (in compliance with their Funk origin), which mainly stay unmatched during the following years. A noticeable drop (−25% compared to TUMPP) is evident with MM (1989), coherently with a Metal-oriented veering, before seeing a singular rise (+26% compared to MM) with BSSM (1991), which comes closer to the early values. OHM (1995) marks another drop (−17% compared to BSSM), furtherly confirmed by *Californication* (1999). Starting from BTW (2002), a relevant increase takes place (+11% compared to *Californication*), which is then followed by further smaller increases with SA (2006) and IWY (2011) and a small decrease with TG (2016), with the four most recent albums scoring similar values, all in compliance with a Mainstream Alternative Rock style.

Speechiness: the starting points of TRHCP (1984) and FS (1985) are general higher (in compliance with their Funk start) compared to the following releases, with the exception of TUMPP (1987) and MM (1989), which score the highest values of the whole discography, indicating the adoption of Hip Hop-like lyrics. A noticeable drop (−54% compared to MM) takes place with BSSM (1991), which is the first album to score a value that mainly stays constant during the band's career, with the only exception of *Californication* (1999), which gets closer to the values of TRHCP and FS thanks to its higher number of tracks with Funk and Hip Hop lyrics (*Around the World*, *Get on Top*, *I Like Dirt*, *Purple Stain*, *Right on Time*).

Acousticness: the first four albums score very diverse values, ranging from the middle one of TRHCP (1984), to a high (+100% compared to TRHCP) one of FS (1985), to the very low ones recorded in the three following albums, from 1987 to 1991. Starting from 1995 and ending in 2011, the band comes close to the average value of Acousticness calculated throughout their whole career (0.7), before noticeably straying from it with TG (2016), which scores the highest value in the discography.

5. Discussion and Conclusions

5.1. Discussion of Results

The proposed quantitative approach to analyze product innovation dynamics in the music industry has allowed us to investigate the evolution of RHCP between 1984 and 2016. The analysis shows that RHCP experimented with diverse styles, genres, and solutions in the early stage of their career, corresponding to the first four albums: the band started off from a mainly Funk and Hip Hop style with TRHCP (1984), before furtherly advancing towards Funk with FS (1985); these first two albums are characterized by lower values of BPM and Energy, and higher values of Danceability and Valence.

Starting with the third album, TUMPP (1987), the band moved towards a heavier style in music, although keeping some distinctive Funk features (mainly in their lyrics): it is the start of a mainly Hard Rock and Metal phase, which is then furtherly amplified in their fourth release, MM (1989).

In their fifth album, BSSM (1991), the result of the recombination of the previously experimented styles can be seen for the first time: the band tries to offset the distinctive Funk traits of TRHCP (1984) and FS (1985), characterized by higher values of Valence and Danceability, and the heavier Hard Rock-oriented traits of TUMPP (1987) and MM (1989), characterized by higher values of BPM and Energy). In doing so, RHCP achieved the first relevant commercial success of their career.

With the sixth album, OHM (1995), a temporary phase of experimentalism opens up for the band: the balance between Funk and Hard Rock previously found in BSSM is now abandoned in favor of a less extreme Rock style. The album is influenced by emerging Alternative Rock trends (Grunge, Shoegaze), which lead to lower values of Energy and Valence.

The seventh album, Californication (1999), follows its predecessor's traits, which resemble the Funk and Hip Hop-oriented ones of the early albums. Californication marks the second time the band achieved a great commercial success and a worldwide recognition (through Grammy Awards nominations, American Music Awards prizes, Brit Awards prizes, and MTV prizes).

Starting with their eighth album, BTW (2002), and as a likely reaction after the fame found with Californication, the band seems to abandon excessive experimentalism and to embrace a stabler and more recognizable style. Besides a major change in Valence from BTW to SA (2006), which is likely due to the increasing exposition to mainstream audiences, and occasional unique values such as the Average Loudness of SA and the Acousticness of TG (2016), the band's changes in style look smaller compared to the past, and their style appears to be less variable and diverse, compliant with the Mainstream Alternative Rock compromise reached starting from OHM (1995) and subsequently refined with Californication (1999).

5.2. Methodological and Theoretical Contributions

In this study, we aimed at developing and demonstrating a quantitative approach to leverage Big Data tools and analytics to investigate product innovation in the music industry. Due to the ongoing digital transformation that is basically affecting every economic sector, firms have the opportunity to unprecedented continuous, reliable, and timely data streams [8]. In turn, this phenomenon is posing new challenges and questions to firms. Indeed, the availability of the so-called Big Data is increasingly pushing firms and researchers to develop new tools and methodologies to exploit it and generate value (e.g., [9–11,50–52]). However, this is not always straightforward, since, usually, traditional data-processing instruments can be scantily efficient and effective when dealing with Big Data [11,53,54], hence calling for new dedicated methodologies. With our study, we contribute to this direction by proposing a solution to leverage Big Data in the music industry to extract valuable information. In particular, we relied on several indicators to show the characteristics of music albums that may affect the customers' perception of these music products. Our

study set the basis to leverage music Big Data to better understand the product innovation dynamics and identify the characteristics of music that mostly appeal the audience.

The scientific value of this research mainly lies in the quantitative nature of the approach. While innovation in other creative industries, such as cinema, has been studied with quantitative methods, music is still elusive given the nature of its products. Music products are difficult to analyze by separating and isolating their inner fundamental elements, such as rhythm, chords progressions, dynamics, and danceability. So far, this is possible only through a complex, qualitative, and highly subjective evaluation of critics. A quantitative approach would provide researchers with a different (and possibly more efficient) tool to make this analysis.

Our study provides theoretical implications. In fact, we apply Big Data analytics to investigate the dynamics of product innovation in a peculiar context as the CCI and, specifically, the music industry. Indeed, the analysis discussed in the paper can offer novel perspectives to understand innovative trajectories in the music industry. Hence, we contribute to the product innovation literature by suggesting how different features of a product, in our case a music album, can be leveraged to better understand product innovation trajectories. In particular, we showed how a successful band as the RCHP continuously innovated their music to achieve customers and critics recognition. Indeed, the recombination of different music genres, highlighted by our analysis, points at a relevant role of recombination strategies to innovate products that appeal customers (see [55]). Furthermore, the recombination of genres also provides music product with a certain degree of uniqueness that may be deemed as a further success factor in product innovation [56].

5.3. Practical Implications

Finally, we suggest how our results can turn out to be useful to both researchers and managers from a practical perspective.

Researchers may have a way to compare the innovation ability of different artists and analyzing the inherent reasons. They may also compare the musical productions of different countries in terms of innovativeness, such as assessing whether British music is more innovative than American music and linking this to cultural and industrial characteristics. Representing artists' innovation paths could be useful to realize what the sources of innovation are, such as whether a band gets inspiration from another genre or tries to rebel to certain musical standards. A quantitative analysis may allow researchers to study what makes people think that an artist is innovative or different from the mainstream. This is important from both the consumer's and the critic's standpoint. What does it make a music be perceived as innovative or even weird by consumers? Is it the rhythm, is it the progression or the variety of chords? And, on the contrary, what does it make music familiar? The same questions can be answered from the critic's perspective. What is the most important differentiator of music styles among those we can extract from an analogic signal?

From a business perspective, our findings may inspire managers in the music industry about how to leverage big data to understand and inform product innovation strategies. For instance, the methodology that we presented could be used to understand the features of the most successful albums and artists, to better comprehend what the customers in the music market ask for and perform benchmarking analyses. Furthermore, this kind of analyses could also be used to spot unexploited market niches that could trigger product innovation to tap specific typologies of customers. In addition, the analysis of albums and artists, but also record producers, could also stimulate the establishment of collaboration to exchange knowledge aiming at innovating musical products, in an open innovation fashion [19]. Collaborations among different artists and record producers are common in the music industry; however, big data can highlight complementarities or even similarities that can be exploited to stimulate the creation of valuable products, as well as their innovation. Managers in music businesses could use our approach to control the way innovation is increasing or decreasing in their companies. Measuring innovation may allow a manager to

allocate resources depending on the innovative ability of artists and the attitude of listeners in different markets.

5.4. Limitations and Further Research

This research presents several limitations. First, we used only a very limited set of musical features, which were those included in the available software platforms. Future research should certainly enlarge this set and possibly build ad-hoc metrics. Second, the identification of the music genres that an artist is inspired by and recombines in her/his music can be done by applying MIR algorithms to specific songs or albums that prove to be a model in that genre for many artists. Third, we will prove, in future studies, that the metrics that we used in this research are aligned with the critics' evaluations. Fourth, our results are based on the analysis of a single rock band (i.e., RHCP). Nonetheless the value of the case study selected to illustrate how to apply MIR tools to analyze product innovation in the music industry, future research may extend the analysis to other bands and/or artists and to distant genres to provide further confirmation of our findings. Despite these limitations, this study represents the first attempt of using MIR to get a quantitative analysis of product innovation in the music industry.

Author Contributions: Conceptualization, M.G. and U.P.; methodology, M.G.; software, M.G.; validation, M.G. and A.C.G.; formal analysis, M.G. and U.P.; investigation, M.G. and A.C.G.; resources, M.G.; data curation, U.P.; writing—original draft preparation, U.P.; writing—review and editing, A.N.; visualization, A.N.; supervision, A.C.G. and A.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Nelson, R.R.; Winter, S.G. *An Evolutionary Theory of Economic Change*; Digitally Reprinted; The Belknap Press of Harvard University Press: Cambridge, MA, USA, 1982; ISBN 978-0-674-27228-6.
- Lampel, J.; Shamsie, J.; Lant, T.K. Toward a Deeper Understanding of Cultural Industries. In *The Business of Culture*; Lawrence Erlbaum Associates: Mahwah, NJ, USA, 2005; ISBN 978-1-4106-1556-5.
- Howkins, J. *The Creative Economy: How People Make Money from Ideas*; Penguin Books Limited: London, UK, 2002; ISBN 978-0-14-028794-3.
- Florida, R. *The Rise of the Creative Class: And How It's Transforming Work, Leisure, Community and Everyday Life*; Basic Books: New York, NY, USA, 2002; ISBN 978-1-877270-57-4.
- Landry, C.; Bianchini, F. *The Creative City*; Demos: London, UK, 1995; ISBN 978-1-898309-16-1.
- Cultural Times. The First Global Map of Cultural and Creative Industries. Available online: <https://en.unesco.org/creativity/files/culturalthimethefirstglobalmapofculturalandcreativeindustriespdf> (accessed on 13 October 2022).
- Hatton, C. IFPI Issues Global Music Report 2021. Available online: <https://www.ifpi.org/ifpi-issues-annual-global-music-report-2021/> (accessed on 13 October 2022).
- Pigni, F.; Piccoli, G.; Watson, R. Digital Data Streams: Creating Value from the Real-Time Flow of Big Data. *Calif. Manag. Rev.* **2016**, *58*, 5–25. [[CrossRef](#)]
- Ardito, L.; Petruzzelli, A.M.; Panniello, U.; Garavelli, A.C. Towards Industry 4.0: Mapping Digital Technologies for Supply Chain Management-Marketing Integration. *Bus. Process. Manag. J.* **2019**, *25*, 323–346. [[CrossRef](#)]
- Ferraris, A.; Mazzoleni, A.; Devalle, A.; Couturier, J. Big Data Analytics Capabilities and Knowledge Management: Impact on Firm Performance. *Manag. Decis.* **2019**, *57*, 1923–1936. [[CrossRef](#)]
- Gupta, M.; George, J.F. Toward the Development of a Big Data Analytics Capability. *Inf. Manag.* **2016**, *53*, 1049–1064. [[CrossRef](#)]
- Pellegrin-Boucher, E.; Roy, P. *Innovation in the Cultural and Creative Industries*; John Wiley & Sons: Hoboken, NJ, USA, 2019; ISBN 978-1-119-68121-2.
- Chen, X.; Liu, C.; Jiang, Y.; Gao, C. What Causes the Virtual Agglomeration of Creative Industries? *Sustainability* **2021**, *13*, 9232. [[CrossRef](#)]

14. Zhang, X.; Dai, J. Cultural and Creative Production in the Era of Globalization: Exploring the Trans-Border Mobility of Chinese Media and Entertainment Celebrities. *Geoforum* **2021**, *120*, 198–207. [CrossRef]
15. Pesce, D.; Neirrotti, P.; Paolucci, E. When Culture Meets Digital Platforms: Value Creation and Stakeholders' Alignment in Big Data Use. *Curr. Issues Tour.* **2019**, *22*, 1883–1903. [CrossRef]
16. Agostino, D.; Arnaboldi, M.; Carloni, E. Big Data for Decision Making: Are Museums Ready? In *Management, Participation and Entrepreneurship in the Cultural and Creative Sector*; Piber, M., Ed.; Springer International Publishing: Cham, Switzerland, 2020; pp. 61–78, ISBN 978-3-030-46796-8.
17. Terras, M.; Coleman, S.; Drost, S.; Elsdon, C.; Helgason, I.; Lechelt, S.; Osborne, N.; Panneels, I.; Pegado, B.; Schafer, B.; et al. The Value of Mass-Digitised Cultural Heritage Content in Creative Contexts. *Big Data Soc.* **2021**, *8*, 20539517211006164. [CrossRef]
18. Lerch, A. *An Introduction to Audio Content Analysis*, 1st ed.; John Wiley & Sons Ltd.: Hoboken, NJ, USA, 2012.
19. Chesbrough, H.W. *Open Innovation: The New Imperative for Creating and Profiting from Technology*; Harvard Business Press: Cambridge, MA, USA, 2003; ISBN 978-1-57851-837-1.
20. Schumpeter, J.A. *Business Cycles. A Theoretical, Historical, and Statistical Analysis of the Capitalist Process*; Mc-Graw Hill: New York, NY, USA, 1939.
21. Moon, H.; Park, J.; Kim, S. The Importance of an Innovative Product Design on Customer Behavior: Development and Validation of a Scale: Importance of an Innovative Product Design on Customer Behavior. *J. Prod. Innov. Manag.* **2015**, *32*, 224–232. [CrossRef]
22. Evanschitzky, H.; Eisend, M.; Calantone, R.J.; Jiang, Y. Success Factors of Product Innovation: An Updated Meta-Analysis: Success Factors of Product Innovation. *J. Prod. Innov. Manag.* **2012**, *29*, 21–37. [CrossRef]
23. Paulson Gjerde, K.A.; Slotnick, S.A.; Sobel, M.J. New Product Innovation with Multiple Features and Technology Constraints. *Manag. Sci.* **2002**, *48*, 1268–1284. [CrossRef]
24. Lee, W.; Yoon, J.; Altmann, J.; Lee, J.-D. Model for Identifying Firm's Product Innovation Dynamics: Applied to the Case of the Korean Mobile Phone Industry. *Technol. Anal. Strateg. Manag.* **2021**, *33*, 335–348. [CrossRef]
25. Verganti, R. Design, Meanings, and Radical Innovation: A Metamodel and a Research Agenda*. *J. Prod. Innov. Manag.* **2008**, *25*, 436–456. [CrossRef]
26. Coccia, M. Technometrics: Origins, Historical Evolution and New Directions. *Technol. Forecast. Soc. Chang.* **2005**, *72*, 944–979. [CrossRef]
27. Christensen, C.M. *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*; Harvard Business Review Press: Cambridge, MA, USA, 2013; ISBN 978-1-4221-9758-5.
28. Grupp, H. The Measurement of Technical Performance of Innovations by Technometrics and Its Impact on Established Technology Indicators. *Res. Policy* **1994**, *23*, 175–193. [CrossRef]
29. Berkowitz, M. Product Shape as a Design Innovation Strategy. *J. Prod. Innov. Manag.* **1987**, *4*, 274–283. [CrossRef]
30. Thompson, P.; Jones, M.; Warhurst, C. From Conception to Consumption: Creativity and the Missing Managerial Link. *J. Organ. Behav.* **2007**, *28*, 625–640. [CrossRef]
31. Askin, N.; Mauskapf, M. What Makes Popular Culture Popular? Product Features and Optimal Differentiation in Music. *Am. Sociol. Rev.* **2017**, *82*, 910–944. [CrossRef]
32. Chapaneri, S.; Lopes, R.; Jayaswal, D. Evaluation of Music Features for PUK Kernel Based Genre Classification. *Procedia Comput. Sci.* **2015**, *45*, 186–196. [CrossRef]
33. Fricke, K.R.; Greenberg, D.M.; Rentfrow, P.J.; Herzberg, P.Y. Computer-Based Music Feature Analysis Mirrors Human Perception and Can Be Used to Measure Individual Music Preference. *J. Res. Personal.* **2018**, *75*, 94–102. [CrossRef]
34. Bogdanov, D.; Wack, N.; Gómez Gutiérrez, E.; Gulati, S.; Herrera Boyer, P.; Mayor, O.; Roma Trepát, G.; Salamon, J.; Zapata González, J.R.; Serra, X. Essentia: An Audio Analysis Library for Music Information Retrieval. In Proceedings of the 14th Conference of the International Society for Music Information Retrieval (ISMIR), Curitiba, Brazil, 4–8 November 2013.
35. Spotify—About Spotify. Available online: <https://newsroom.spotify.com/company-info/> (accessed on 7 December 2022).
36. De Prisco, R.; Guarino, A.; Lettieri, N.; Malandrino, D.; Zaccagnino, R. Providing Music Service in Ambient Intelligence: Experiments with Gym Users. *Expert Syst. Appl.* **2021**, *177*, 114951. [CrossRef]
37. Duman, D.; Neto, P.; Mavrolampados, A.; Toiviainen, P.; Luck, G. Music We Move to: Spotify Audio Features and Reasons for Listening. *PLoS ONE* **2022**, *17*, e0275228. [CrossRef] [PubMed]
38. Khan, F.; Tarimer, I.; Alwageed, H.S.; Karadağ, B.C.; Fayaz, M.; Abdusalomov, A.B.; Cho, Y.-I. Effect of Feature Selection on the Accuracy of Music Popularity Classification Using Machine Learning Algorithms. *Electronics* **2022**, *11*, 3518. [CrossRef]
39. Mariani, M.M.; Fosso Wamba, S. Exploring How Consumer Goods Companies Innovate in the Digital Age: The Role of Big Data Analytics Companies. *J. Bus. Res.* **2020**, *121*, 338–352. [CrossRef]
40. Mariani, M.M.; Nambisan, S. Innovation Analytics and Digital Innovation Experimentation: The Rise of Research-Driven Online Review Platforms. *Technol. Forecast. Soc. Chang.* **2021**, *172*, 121009. [CrossRef]
41. Towse, R. Dealing with Digital: The Economic Organisation of Streamed Music. *Media Cult. Soc.* **2020**, *42*, 1461–1478. [CrossRef]
42. Hagen, A.N. Datafication, Literacy, and Democratization in the Music Industry. *Pop. Music Soc.* **2022**, *45*, 184–201. [CrossRef]
43. Sarkar, M.; Roy, A.; Badr, Y.; Gaur, B.; Gupta, S. An Intelligent Music Recommendation Framework for Multimedia Big Data: A Journey of Entertainment Industry. In *Multimedia Technologies in the Internet of Things Environment*; Kumar, R., Sharma, R., Pattnaik, P.K., Eds.; Studies in Big Data; Springer: Singapore, 2022; Volume 2, pp. 39–67, ISBN 9789811638282.

44. Mumic, N.; Leodolter, O.; Schwaiger, A.; Filzmoser, P. Scale Invariant and Robust Pattern Identification in Univariate Time Series, with Application to Growth Trend Detection in Music Streaming Data. In *Artificial Intelligence, Big Data and Data Science in Statistics: Challenges and Solutions in Environmetrics, the Natural Sciences and Technology*; Steland, A., Tsui, K.-L., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 25–50, ISBN 978-3-031-07155-3.
45. Glaser, B.G.; Strauss, A.L. *The Discovery of Grounded Theory: Strategies for Qualitative Research*; Aldine transaction: Piscataway, NJ, USA, 1967; ISBN 978-0-202-30260-7.
46. Yin, R.K. *Case Study Research: Design and Methods*; SAGE: Thousand Oaks, CA, USA, 2003; ISBN 978-0-7619-2552-1.
47. Eisenhardt, K.M. Building Theories from Case Study Research. *Acad. Manag. Rev.* **1989**, *14*, 532. [[CrossRef](#)]
48. Sheffield, A.M.; Dolan, J.; Aaron, C. The 40 Greatest Red Hot Chili Peppers Songs. *Rolling Stone*, 11 April 2022.
49. Shanfeld, E.; Willman, C. Red Hot Chili Peppers on John Frusciante’s Return for New Album—And Their 40-Year Journey From ‘Hollywood Street Kids’ to a Walk of Fame Star. *Variety*, **2022**.
50. Buganza, T.; Trabucchi, D.; Pellizzoni, E. Limitless Personalisation: The Role of Big Data in Unveiling Service Opportunities. *Technol. Anal. Strateg. Manag.* **2020**, *32*, 58–70. [[CrossRef](#)]
51. Urbinati, A.; Bogers, M.; Chiesa, V.; Frattini, F. Creating and Capturing Value from Big Data: A Multiple-Case Study Analysis of Provider Companies. *Technovation* **2019**, *84–85*, 21–36. [[CrossRef](#)]
52. Simsek, Z.; Vaara, E.; Paruchuri, S.; Nadkarni, S.; Shaw, J.D. New Ways of Seeing Big Data. *Acad. Manag. J.* **2019**, *62*, 971–978. [[CrossRef](#)]
53. Wang, H.; Xu, Z.; Fujita, H.; Liu, S. Towards Felicitous Decision Making: An Overview on Challenges and Trends of Big Data. *Inf. Sci.* **2016**, *367–368*, 747–765. [[CrossRef](#)]
54. Günther, W.A.; Rezazade Mehrizi, M.H.; Huysman, M.; Feldberg, F. Debating Big Data: A Literature Review on Realizing Value from Big Data. *J. Strateg. Inf. Syst.* **2017**, *26*, 191–209. [[CrossRef](#)]
55. Savino, T.; Messeni Petruzzelli, A.; Albino, V. Search and Recombination Process to Innovate: A Review of the Empirical Evidence and a Research Agenda: Search and Recombination Process. *Int. J. Manag. Rev.* **2017**, *19*, 54–75. [[CrossRef](#)]
56. Messeni Petruzzelli, A.; Savino, T. Search, Recombination, and Innovation: Lessons from Haute Cuisine. *Long Range Plan.* **2014**, *47*, 224–238. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.