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Multidimensional Analysis Integrated with Multicriteria Decision-making in Data Warehouse Framework

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***Abstract* - In today's data-driven environments, due to rise in data complexity and manageability concerns, data warehouses offers to store, integrate, and analyze large volume of historical data for informed decision-making. This study presents the design and implementation of a multidimensional analysis and ranking framework for assessing artist popularity in the digital music market using a data warehouse-driven methodology. ETL processes are utilized to convert data from GitHub into a star schema-based warehouse, named MuDW, in SQL Server. This ensures that fact and dimension tables are logically normalized to facilitate multidimensional queries and insights. Microsoft Visual Studio creates an OLAP cube (MUSIC_CUBE) to support multidimensional analysis across temporal, geographical, and categorical dimensions such as artist_album, date, and location. Furthermore, the analytical results derived from OLAP are combined with the order preference by similarity to ideal solution (TOPSIS) method, and the entropy weight method (EWM) is used to generate criterion weights, to determine artist rankings based on multiple quantitative factors related to listener engagement and artist revenue. Further, a 3D OLAP cube visualization using Python is developed to show artist, genre popularity distribution over time and location. This hybrid framework effectively integrates data warehousing, OLAP processing, and multi-criteria decision-making to provide actionable insights on artist popularity trends of strategic value for decision making for music platforms and industry stakeholders.**

Keywords: Data warehouse, multi-dimensional analysis, music data, OLAP cubes, MDX queries.

I. INTRODUCTION

A data warehouse is a centralized repository of data collected from heterogeneous sources that help in decision-making, support structured query execution, business intelligence operations, analytical reporting's and decision making process. It enables to perform effective queries, store historical data, and multidimensional analysis to uncover hidden patterns and trends.

Music has long been acknowledged for its therapeutic impacts on the human intellect, providing cognitive relaxation, regulating emotions, and stress reduction (De Witte et al., 2020 and Nwokenna, Sewagegn & Falade (2022). Leveraging on this psychological effect, the data analytics in music provides understanding listener behavior, enhancing listener engagement and assessing financial success of their work. By exploring listener preferences, streaming patterns, and behavioral trends, stakeholders can optimize marketing strategies, and predict emerging music trends, driving revenue growth and audience retention.

An emerging application of data warehousing approach lying in the music domain can further help in understanding audience behaviour, tracking artist performance, and supporting music-based emotional wellbeing from the huge amount of music data. Kumar, Kushwah& Singh (2025) have shown that a data warehouse for music data facilitates the storing of multi-dimensional data in a single data repository efficiently. In this work, a music data warehouse is designed to deduce artist popularity based on revenue generated through track or album purchases, customer engagement, and quantity of album sold. This consolidated structure further facilitates enhanced analysis using complex queries. Such data-based insights are essential for music industries since they enable them to track the emerging trends and drive the strategic decisions in the increasingly competitive sectors.

II. BACKGROUND

A data warehouse integrates heterogeneous data from multiple operational and transactional sources into a unified platform to provide organizations a unified and consistent view of organizational data enabling, effective trend analysis, improved reporting, and enhanced decision-making capabilities. Bouaziz, Nabli & Gargouri (2021) integrating open COVID-19 datasets into data warehouse structure to support decision-making under dynamic and evolving data conditions. Ahmadi (2023) and Padron-Uy et al. (2025) explored the way machine learning enhances data warehouse performance by optimizing queries and automating management tasks. Gunes & Birgin (2023) showed the significance of data warehouse enhances the ability to observe

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the learner behavior, generate performance reports in multidimensional domain, and support data-driven enhancements in distance education platforms. Maaitah (2023) demonstrated that business intelligence tools play important role in decision making, transforming organizational data into decision oriented insights and overall performance. The study indicated that BI-driven analytical insights improve client's needs and performance suitably. Yadav, Bhandari & Poudel (2023) demonstrated a well-designed academic data warehouse integrates dispersed student and administrative data, improves information accessibility, and enhances decision making by secure analytical reporting. Chilukoori, Gangarapu & Kadiyala (2024) explored the data warehousing challenges and the opportunities such as data quality, and scalability, improved risk management, fraud detection and manage vast amount of institutional data. Lado Río (2024) and Szabat Fernández (2024) demonstrated that integrating multiple sources like Spotify and Music Brainz through extract-transform-load processes in data warehouse creates unified and analyzable datasets. Lyu, Craig, Reilly & Taniar (2025) showed the contribution of data warehouse in clinical environments to improve patient-care analytics, resource management, and clinical research by enabling healthcare outcomes. Sanjeetha & Asanka (2025) established a cost-effective and low-complexity data analytics infrastructure for small and medium-sized enterprises to facilitate their transition into data-driven organizations. They also demonstrated cost effective data warehouse architecture that enables small and medium-sized enterprises to integrate transactional data, improve analytical capabilities, and support business decisions.

In today's digital era, music is not only a source of entertainment but it also enables significant cognitive and psychological benefits for individuals in their daily lives. The data analytics in music domain has become necessary as it facilitates deeper understanding of listener behavior, popularity modelling, generate personalized music recommendations, trend prediction in audience preferences, and marketing strategies. By Evaluating streaming patterns, geographic listening behaviors, and artist popularity measures, organizations can improve decision-making such as targeted marketing & advertising, content curation and artist support, and revenue optimization. The impact of background music on drivers' behaviours, mood, and emotion changes using a driving simulator can in turn influence especially when the induced emotional valence is negative (Navarro et al., (2023)).Aasim (2024) and Chatterjee (2024) highlighted music's therapeutic potential to improve general wellbeing. According to the study, music therapy helps with physical rehabilitation, promotes relaxation, controls emotions, lowers tension, and eases pain. Xian, Zhang, Zheng & Wang (2024) analyzed the cognitive health benefits of listening music during the quarantine period. They highlighted listening to music significantly enhanced emotional relaxation, stress reduction, and overall mental well-being. Yingjie & Mingda (2024) and Feng & Wang (2025) demonstrated the impact of music therapy one motional resilience, well-being and employability. The study also highlighted that music can be a structured therapeutic mechanism to promote emotional stability, mental health, and career-related outcomes.

In the current era, organizations increasingly prefer multidimensional analysis to examine data from different perspectives like time, location, and product classification to uncover trends, hidden patterns, and strategic decision making. Such multidimensional analysis is only possible through online analytical processing (OLAP) technologies, which supports fast, interactive, and hierarchical data analysis for decision making. OLAP is a powerful technology that transforms integrated historical data into multidimensional domain. It allows users to enhance decision-making in a data warehouse by enabling multidimensional analysis. OLAP effectively processes large datasets that enables Interactive data exploration, performance evaluation, trend identification, and valid strategic decision-making. Najm et al. (2022) implemented an educational data mart and then apply OLAP mining to develop multidimensional cubes for analyzing student performance in academic data. The study showed OLAP-based outcomes combined with various data mining algorithms to predict student performance and highlights at risk learners. Predictive modeling and OLAP-based multidimensional analysis were integrated to improve business intelligence forecasting and decision-making (Abrarov & Khudaybergenov, (2024)). Alkhanifer & Alzubi (2024) proposed a big data querying and correlative analytical techniques to evaluate complex business intelligence queries over huge, heterogeneous data groups. The study introduced the OLAP framework to enhance operations such as aggregation, filtering, roll-up, and drill-down for multiple database perspectives. This research identified different big data techniques for a business and provides various corporate business continuity determinants that influence strategic decisions.

Massive amounts of heterogeneous data from digital music platforms such as social media, mobile apps, and user interaction logs have been produced by music consumption in recent years, leading to extremely dispersed and unstructured data. Such dispersed data creates significant challenges for combined analysis, making it necessary to integrate these disparate sources into a centralized repository. This rapid growth of digital music platforms has further amplified the demand for robust data architectures to store, process, and analyze user listening behavior. With surges across both volume and complexity presents a formidable challenge in

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managing music data effectively. Unified storage, multidimensional analysis, and the extraction of significant insights and patterns pertaining to listener preferences, genre trends, and artist performance are all made possible by a well-designed music data warehouse. Data warehouse has been widely used in various fields (Cormier et al., 2025, Lyu, Craig, Reilly & Taniar (2025) and Lv (2025)); however, its application in the music domain remains relatively underexplored. Innovative strategies that can support sophisticated analytics and personalized insights suited to the ever-changing digital music industry are needed to address these issues.

Inspired by existing literature, efforts have been made to develop a data warehouse that will enable music data (MD) analysis of listener preferences and changes in music trends while facilitating the storage, analysis, and retrieval of massive amounts of music-related data. In order to support data-driven decision-making and MCDM techniques, OLAP queries will be used to provide multidimensional insights into listener preferences and music trends.

III. METHODOLOGY

The primary goal of this research study is to evaluate the artist popularity as well as genre popularity based on the various criteria. To achieve this research study goal, a music data warehouse is generated, and multi-dimensional analysis is performed by combining OLAP and multi-criteria analysis techniques in a data warehouse framework. The methodological steps include:

A. Collecting the data,
B. Designing the data warehouse,
C. Designing the OLAP cube,
D. Querying the data, and
E. Ranking the artists.

A. Collecting the Data

The dataset for the study is taken from *MusicStoreDataAnalysis* at the GitHub repository that contains a normalized schema of a digital music store. The dataset includes customer, artist, track, album, playlist, playlist_track, genre, media_type, and invoice data, which was used to perform the dimensional modeling in the warehouse. Figure 1 illustrates the ER diagram of the music data.

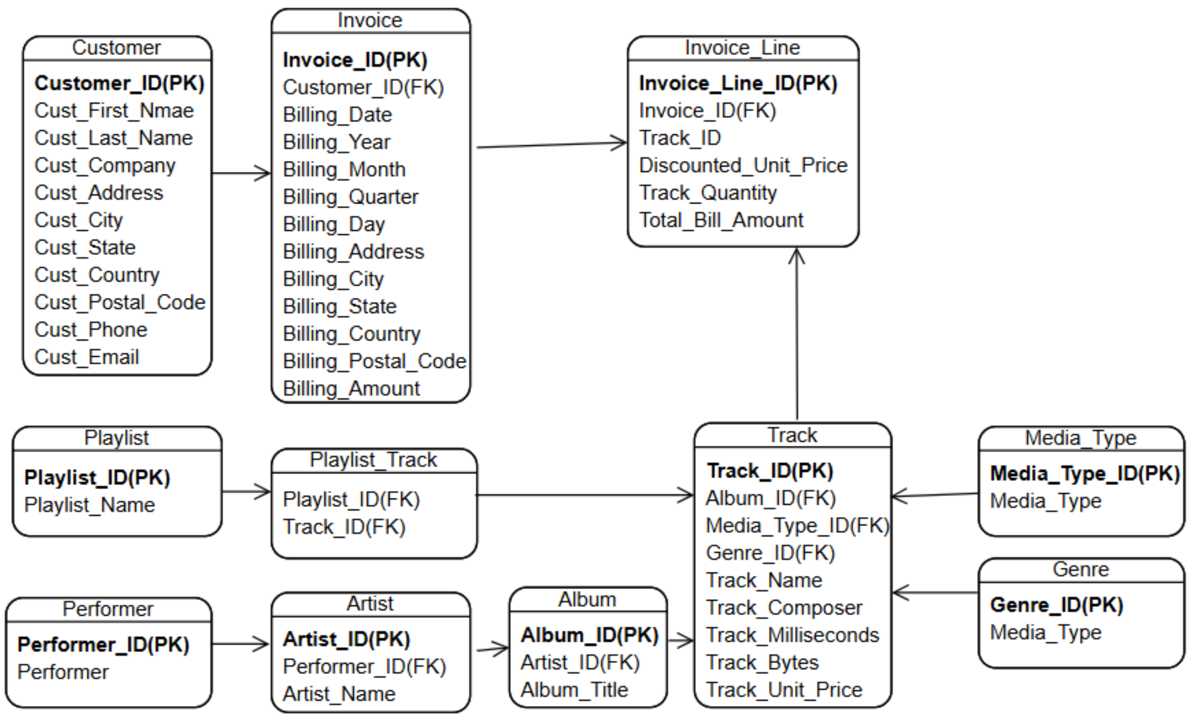

Figure 1: ER Diagram for the music data

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B. Designing the music data warehouse

A music data warehouse (MuDW) is designed to store and analyzed at a related to artists, music types, and listener behavior from the designed database. This study follows the approach of Kimball & Ross (2010) for developing the analytical framework. The steps to design the MuDW are as follows:

a) **Choosing the business process:** The main goal to develop the MuDW is to perform popularity analysis, with the focus on evaluating artist rankings, based on the number of customers listening the artist, revenue generated and total track quantity purchased. The required tables and attributes are identified for analytical processing. Key entities containing descriptive attributes and transactional details are shown in the ERD.

b) **Declaring the grain:** The grain supports detailed analysis of artist overtime (year, quarter, month, day) and across geographic hierarchies (country, state, city) for both customer and billing locations. The fact table granularity of the MuDW is shown in Table 1.

Table 1: Fact Table Granularity

Field	Description
Time	Each fact record is associated with a specific point in time (Year, Quarter, Month, Day) from *Dim_Date*.
Customer	Each fact record represents a purchase made by a single customer, linked to *Dim_Customer* for demographic and profile analysis.
Location	Each fact record is linked to *Dim_Location* for customer and billing hierarchies (Country → State → City).
Track	Each fact record is linked to Dim Track, capturing details like track details.
Artist	Each fact record is linked to *Dim_Artist_Album*, capturing the artist's name and associated album details.
Measures	Fact records capture measures (quantity, unit price, total revenue, and total invoice), fully additive across all dimensions.

c) **Identifying the dimension:** The dimension tables are identified from the music database. These metrics are selected for assessing music popularity across different users, time periods, genres, locations, and artist popularity. To ensure consistency and integration through the data warehouse, these dimensions are confirmed by establishing standardized attribute formats and well defined hierarchies. The created dimension tables for MuDW are shown in Figure 2. Appropriate hierarchies are created within dimensions Dim_Date, and Dim_Location to enable OLAP operations. A bridge table, Bridge_Playlist_Track, is also integrated into the cube design to handle the many-to-many relationship between playlists (Dim_Playlist) and tracks (Dim_Track) and to ensure that playlist-level and track-level analyses are performed without data redundancy.

d) **Choosing the fact:** A fact table, *Fact_Music*, is constructed (Figure 2) to serve as a central repository of measurable and quantitative data and enables analytical operations across various dimensions. This table contains the surrogate keys from the associated dimension tables along with key measures like *Discounted_Unit_Price*, *Track_Quantity*, *Total_Bill_Amount*, and *Billing_Amount*. The *Fact_Music* table stores pre-calculated as well as derived measures to improve analytical performance. The measures *Discounted_Unit_Price* and *Track_Quantity* are taken from the *invoice_line* table in the music database. From these, a derived measure *Total_Bill_Amount* is calculated using the formula (*Discounted_Unit_Price* * *Track_Quantity*). In contrast, the *Billing_Amount* measure represents the overall invoice amount directly obtained from the *invoice* table of the database.

e) **Choosing the duration of database:** The dataset used for the data warehouse spans from 2017 to 2020, obtained from the GitHub repository. This period is selected to capture multi-year patterns in music data and offer a solid foundation for temporal analysis in the system.

f) **Decide the physical design:** The main goal of the physical design phase is focused on implementing the ETL process to transition data from the source database to the data warehouse.

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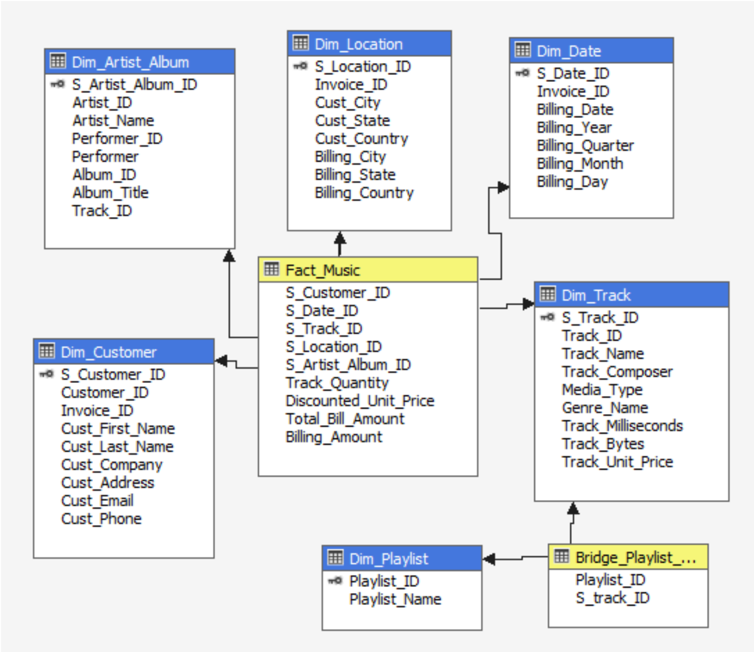

Figure 2: The star schema for MuDW

ETL Process: The ETL process includes:

Extract phase

- Extracting pre-calculated and derived measures from the *invoice* and *invoice_line* tables,
- Identifying surrogate key mappings and defining join paths between dimension tables (*Dim_Customer*, *Dim_Artist_Album*, *Dim_Location*, *Dim_Date*, *Dim_Track*) and the fact table (*Fact_Music*) to maintain referential integrity and support the star schema design.

Transform phase

- Cleaning the extracted data by handling missing values and removing inconsistencies from source tables.
- Eliminating null records and standardizing data types and formats to ensure consistency.
- Creating surrogate keys for all dimension tables to uniquely identify records and ensure stable references in the fact table.
- Deriving new attributes to enhance analytical capabilities, such as extracting *year*, *month*, *day*, and *quarter* from *invoice_date* to construct *Dim_Date*.
- Merging artist and album details to create a unified Dim_Artist_Album dimension.
- Joining multiple source tables to create enriched dimension tables.
- Standardizing column names and formats according to data warehouse conventions to simplify OLAP modeling.
- Validating all transformations to ensure data correctness and consistency before loading into the warehouse.

Load phase

- Inserting the transformed and cleaned data into the data warehouse schema.
- Populating the fact table with appropriate measures and foreign keys from the related dimension tables.
- Using the refined and cleaned data from the warehouse as input for OLAP cube generation.

The music database and data warehouse are both developed using SQL, enabling full control over data transformation and integration. The SQL query to create the dimension table Dim_Customer is shown below. Similarly other dimension tables are created.

```
CREATE TABLE Dim_Customer (
    S_Customer_ID int identity(1,1) primary key,
    Customer_IDvarchar(30),
```

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```
    invoice_idvarchar(10),
    First_Namevarchar(50),
    Last_Namevarchar(50),
    Company varchar(50),
    Address varchar(50),
    Email varchar(50),
    Phone varchar(50));

insert into Dim_Customer (Customer_ID,
  invoice_id,First_Name,Last_Name,Company,Address,Email, Phone)
  SELECT c.Customer_ID, i.invoice_id, c.First_Name,c.Last_Name,c.Company,c.Address,
    c.Email, c.Phone
  FROM Customerc,invoice i
  Wherec.customer_id=i.customer_id;
```

The SQL query to create *Fact_Music* is shown below.

```
create table Fact_music (
    s_customer_id int,
    s_date_id int,
    s_track_id int,
    s_location_idint ,
    s_artist_album_id int,
    quantity int,
    unit_pricenumeric(3,2),
    Total_Revenuenumeric(3,2),
    total numeric(4,2),
    foreign key (s_customer_id) references dim_customer(s_customer_id),
    foreign key(s_date_id) references dim_date(s_date_id),
    foreign key(s_track_id) references dim_track(s_track_id),
    foreign key(s_location_id) references dim_location(s_location_id),
    foreign key(s_artist_album_id) references dim_artist_album(s_artist_album_id));

  INSERT INTO Fact_music
    (s_customer_id,s_date_id,s_track_id,s_location_id,s_artist_album_id,quantity,uni
    t_price,Total_Revenue,total)
    SELECT dc.s_customer_id,dd.s_date_id, dt.s_track_id,dl.s_location_id,
      daa.s_artist_album_id,il.quantity,il.unit_price,il.Total_revenue,i.total
    from dim_customer dc
      INNER JOIN customer dm on dc.customer_id = dm.customer_id
      INNER JOIN invoice_line il on dc.invoice_id = il.invoice_id
      INNER JOIN dim_track dt on il.track_id = dt.track_id
      INNER JOIN invoice i on dc.customer_id = i.customer_id and il.invoice_id =
        i.invoice_id
      INNER JOIN dim_date dd on i.invoice_id = dd.invoice_id and il.invoice_id =
        dd.invoice_id
      INNER JOINdim_location dl on i.invoice_id = dl.invoice_id
      INNER JOIN dim_artist_albumdaa on dt.track_id = daa.track_id
      INNER JOIN album alb on daa.album_id = alb.album_id
      INNER JOIN artist art on alb.artist_id = art.artist_id
      INNER JOIN track tr on il.track_id = tr.track_id and alb.album_id =
        tr.album_id
      INNER JOIN dim_tracktrk on tr.track_id = trk.track_id
      INNER JOIN media_type mt on tr.media_type_id = mt.media_type_id
```

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```
INNER JOIN genre gr on tr.genre_id = gr.genre_id
```

C. Designing the OLAP Cube

In the next phase, an OLAP cube named *MUSIC_CUBE* is created using visual studio, while the data warehouse is stored in SQL server. The OLAP cube is developed by configuring appropriate dimensions, measures, and hierarchies to enable multidimensional analysis. Once the cube is created, it also allows users to access complex analytical results by slicing, dicing, and aggregating data across various dimensions and hierarchies. MDX is used to query and analyze multidimensional data stored in OLAP cubes. MDX plays a crucial role in performing operations like ranking, filtering, and trend analysis within the cube environment.

D. Multi-criteria evaluation

After obtaining the analytical results using MDX queries by combining entropy weight method (EWM) and TOPSIS methodology to rank artists based on their proximity to the ideal solution. This combinative strategy helps in the decision making-process and measures the level of disorder in data.

D.1 Entropy Weight Method (EWM): The EWM is a technique used to determine the relative importance of evaluation criteria. It measures the degree of disorder in the data and supports the decision-making process by providing more weights to criteria with more variability and lower weights to those with higher uniformity. It provides weights objectively depend on the degree of variation related with each criterion. EWM is employed to compute the weights for key factors namely C1: *Customer reach*, C2: *Total_Bill_Amount* and C3: Total *Track_quantity* sold which are subsequently integrated into the TOPSIS approach to rank the artists and decision evaluation.

The following steps of EWM are applied to obtain their respective weights of the given criteria, as outlined below.

i.1 Construction of the Decision Matrix

In the first step, a decision matrix X= [$\boldsymbol{x_{ij}}$] is constructed by considering the three criteria that reflect artist popularity.

$$X=\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ & \vdots & \\ x_{m1} & x_{m2} & x_{m3} \end{bmatrix} \qquad (1)$$

Where each element$\boldsymbol{x_{ij}}$ represents the performance value of artist *i* on criterion *j*, where *i=1,…,*m *j* =1,2,3.In this study, the criteria are defined as follows

- C1: *Customer Reach*
- C2: *Total_Bill_Amount*
- C3: *Track_Quantity*sold
- m= Number of artists
- n=number of criteria

i.2 Normalization of the Decision Matrix

Since the three criteria have different scales and units, the raw data is normalized to ensure comparability. The normalized value of artist *i* under criterion *j*, denoted as $\boldsymbol{P_{ij}}$, is calculated using Eq. (1).

$$P_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}}} \quad , i=1,2,\ldots.,m; j=1,2,\ldots,n \qquad (2)$$

i.3 Entropy Calculation for Each Criterion

The entropy measure is employed to assess the degree of disorder or uniformity of each criterion across all artists. It is calculated as:

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$$\boldsymbol{E_{ij}} = -\,\mathrm{K}\sum_{i=1}^{m} \boldsymbol{P_{ij}} * \ln(\boldsymbol{P_{ij}}) \qquad \textbf{(3)}$$

Here K=1/ln (m) and m denotes the total number of artists, where $\boldsymbol{Pij}$ is obtained from Eq. (2). A higher entropy value signifies greater uniformity (lower variability) and thus indicates lower importance of the corresponding criterion.

i.4 Degree of Diversification

The degree of divergence for each criterion is calculated as

$$\boldsymbol{d_{ij}} = 1 - \boldsymbol{E_{ij}} \qquad \textbf{(4)}$$

Here $\boldsymbol{E_{ij}}$ is obtained from Eq. (3) and higher $\boldsymbol{d_{ij}}$ value indicates that the corresponding criterion (*Customer reach*, *Total_Bill_Amount* and*Track_Quantity sold*) provides greater differentiation among artists.

i.5 Determination of Criteria Weights

Eventually, the normalized weight of each criterion is computed by Eq. (4)

$$\mathbf{W}_{ij} = \frac{\mathbf{d}_{ij}}{\sqrt{\sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{d_{ij}}}} \qquad \textbf{(5)}$$

The relative importance of each criterion in determining artist popularity is shown by these resulting weights.In this study, these weights objectively capture the impact of *Customer reach*, *Total_Bill_Amount*, and *Track_Quantity* Sold, thereby omitting subjectivity in assigning importance.

D.2 TOPSIS: It is a broadly used multi-criteria decision-making approach that ranks alternatives based on their proximity to an ideal solution and distance from a negative ideal. It is appropriate for business, engineering, and analytics decision-making scenarios since it is computationally efficient, simple to understand, and able to manage conflicting criteria. The artists' ranking procedure includes:

ii.1 Selecting the criteria: Three important performance criteria’s are used to rank each artist:

C_1:*Customer_Reach*(Benefit)

C_2:*Total_Bill_Amount*(Benefit)

C_3:*Track_Quantity*sold(Benefit)

These criteria are selected based on their impact on artists’ popularity and business performance.

ii.2 Constructing the Decision Matrix (D): Matrix D is constructed where each row represents an artist, and each column is a decision criterion. The decision matrix D is given as:

$$\mathrm{D}=\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ & \vdots & \\ x_{m1} & x_{m2} & x_{m3} \end{bmatrix} \qquad (1)$$

Where first column represents customer reach of artist *i*, second column total bill amount for artist *i*, and third column Total track quantity sold for artist *i*. This resulted in a 130 × 3 matrix.

ii.3 Normalize the Decision Matrix: The matrix D is normalized to bring all criteria to a comparable scale. This gives the normalized matrix N = $[n_{ij}]_{130\times3}$.

ii.4 Computing the weights of the Criteria: To determine the importance of the criteria, EWM is employed to compute the weights of these criteria. The values obtained are w_1=0.3778,w_2=0.2834,andw_3=0.3387.

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ii.5 Constructing the Weighted Normalized Decision Matrix: The weighted normalized decision matrix is then constructed using formula (2):

$$v_{ij} = w_j * n_{ij} \qquad (2)$$

This gives matrix V = $[v_{ij}]_{130\times3}$.

ii.6 Determining the Positive and Negative Ideal Solutions: The positive and negative ideal solutions are determined using formula (3).These represent the best and worst performance levels for each criterion across all artists.

$$A^{+} = \{Max(V_{1j}, V_{2j}, \ldots.. V_{mj})|j = 1,2,3\} \qquad (3)$$

$$A^{-} = \{Min(V_{1j}, V_{2j}, \ldots.. V_{mj})|j = 1,2,3\}$$

ii.7 Calculating the Separation Measures: The separation of each artist is now computed as:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^{+})^2} \qquad (4)$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^{-})^2}$$

Where S_i^{+} and S_i^{-} are the Euclidean distances of artist i from the positive and negative ideal points, respectively.

ii.8 Calculating the Relative Closeness to the Ideal Solution: The relative closeness of each artist to the ideal solution is given by:

$$C_i = \frac{S_i^{-}}{S_i^{-} + S_i^{+}} \qquad (5)$$

A higher C_i value indicates that the artist is closer to the ideal performance across all criteria.

ii.9 Ranking the Artists: All artists are ranked in descending order of C_i. The artist with the highest score is considered the best based on combined popularity on all criteria.

IV. THE MUDW

The developed framework (MuDW) demonstrates the end-to-end integration of a music database with a multidimensional OLAP environment. Initially, raw music data are processed through an ETL and stored in a MuDW data warehouse, which serves as the foundation for cube construction. Multidimensional insights are then extracted using MDX queries on the music cube which then gets processed by the TOPSIS method in the artist ranking model to compute and form artist rankings. The MuDW framework is as illustrated in Figure 5. The framework consists of following components:

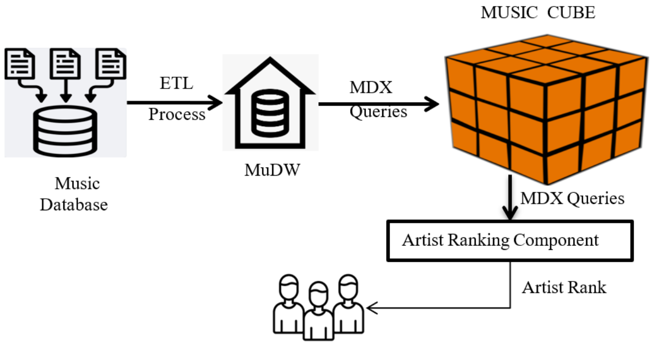

Figure 3: The MuDW framework

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a) **Music Database:** SQL Server is used to store the data from GitHub in the music database. The database stores raw data about music streaming such as customer information, artist, album, track, location and transactional details. The structured dataset sourced from an open-access GitHub repository is used in the study, and then it is converted into a data warehouse schema for analytical processing. The structured database included 275 artists, each uniquely identified by an Artist_ID. Among them, 204 artists are mapped with the album table, which shows that they are associated with one or more albums. Nevertheless, 130 artists only showed active engagement in listening as well as quantifiable sales transactions. These 130 artists served towards the assessment of the key analytical measures like *Customer Reach*, *Total_Bill_Amount* and Total *Track_Quantity* purchased. The other 74 artists (204-130) although they are presented in the album table, did not make any contribution to the transaction and so they are not active or passive participation in the sales process. These refinements of such data made the analytical results reliable and accurate since only active contributors in the dataset are considered.

b) **Data Warehouse:** MuDW data warehouse is created by performing ETL processes on the MUSIC database to extract, transform and load dimensional data into a structured repository. This part of the framework is designed as fact and dimension tables through SQL.

c) **MUSIC OLAP Cube:** The OLAP cube MUSIC is created in visual studio to conduct effective multidimensional analysis on the MuDW data warehouse. The cube provides such insights as customer reach by artist, top genre by country and year, and top performer by country.

d) **Artist ranking model:** The collected outcomes generated by MDX queries are combined with the TOPSIS approach to evaluate and rank artists according to multiple criteria including *Customer_Reach*, *Total_Bill_Amount*, and Total *Track_Quantity* sold.

e) **Data Visualization:** At the final step, the designed framework presents the rankings of artists to end users by combining the TOPSIS approach with the analytical results of MDX queries. The final results support strategic decisions in the music streaming domain, such as performance tracking, marketing, and data-driven decision-making.

V. MULTIDIMENSIONAL ANALYSIS OF THE MUSIC DATA

OLAP environment supports the multidimensional analysis of data which can be analyzed in many dimensions like time, location, and categorical attributes using MDX queries. In this research, it allows exploration of artist performance, genre popularity and listening trends with efficiency by slicing, dicing and aggregating data across various dimensions and hierarchies. The popularity of artists based on different criteria, including *Customer Reach*, *Total_Bill_Amount*, and total *Track_Quantity* sold, utilize pre-calculated and derived measures of the OLAP cube to offer multidimensional views of music engagement. Whereas Customer Reach indicating the scope of engaged listeners, *Total_Bill_Amount* reflects the frequency of buying, and track quantity sold reflects the overall sales volume, but none of these measures are always consistent, which means that a single-point of ranking should be adopted.

To address this issue, the TOPSIS method can be used, which enables multi-criteria decision-making by considering all aspects. By integrating these three criterions into a single framework, TOPSIS offers a more comprehensive and reliable representation of final artist ranking compared to single-criterion analysis.

Following are the steps to perform multidimensional analysis to determine *Customer Reach*, *Total_Bill_Amount*, and total *Track_Quantity*.

I) Determining customer reach based on artist listening engagement

This section presents how many customers associated with a specific artist that enables the artist's popularity based on customer reach.

MDX Query: 1

```
SELECT
NON EMPTY {[Measures].[Customer Reach] } ON COLUMNS,
NON EMPTY
     {
FILTER(
            ([Dim Artist Album].[Artist Name].[Artist Name].ALLMEMBERS *
             [Dim Artist Album].[Artist ID].[Artist ID].ALLMEMBERS *
```

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```
                [Dim Artist Album].[Performer].[Performer].ALLMEMBERS),
                [Measures].[Customer Reach] >= 1
            )
        } ON ROWS
    FROM [MUSIC_CUBE];
```

The output of the above MDX query presents distinct customers connected to each artist and performer to calculate customer reach. In order to display listener interaction patterns and popularity trends across artists and performers, it further filters and extracts artist-specific attributes.

Artist Name	Artist ID	Performer	Customer Reach
The Rolling Stones	A142	Band	47
U2	A150	Band	46
Foo Fighters	A84	Band	44
Green Day	A54	Band	44
Nirvana	A110	Band	44
Queen	A51	Band	43
AC/DC	A01	Band	42
Guns N Roses	A88	Band	42
Metallica	A50	Band	42
R.E.M.	A124	Band	42

Figure 4: MDX Query Output Displaying the Top 10 Artists Based on Distinct Customer Count

Finally, figure 4 shows only the top 10 artists with the highest customer reach values, thus presenting a focused view of the most well-known artists while excluding the remaining records from visualization as per the applied ranking criteria. The outcome displays key artist attributes such as artist name, artist ID, and performer type, along with the computed customer reach measure. Such as, *The Rolling Stones* contains the highest customer reach (47), followed by *U2* (46), *Foo Fighters*, *Green Day*, and *Nirvana* (44 each), showing high levels of customer engagement. These findings show that many artists maintain a broad listener base, which may not directly correspond to their positions in revenue-based rankings. This highlights the significance of customer reach as a complementary metric for evaluating artist popularity and audience reach.

DWH Query: 1

```
SELECT DISTINCT
    dc.Customer_ID,
    dc.Cust_First_Name + ' ' + dc.Cust_Last_Name AS Customer_Name
FROM Fact_Musicfm
JOIN
    Dim_Artist_Albumdaa
    ON fm.S_Artist_Album_ID = daa.S_Artist_Album_ID
JOIN
     Dim_Customer dc
     ON fm.S_Customer_ID = dc.S_Customer_ID
WHERE
    daa.Artist_Name = 'The Rolling Stones';
```

A DWH-based SQL query is executed, to validate the MDX-derived customer reach value of 47 for *The Rolling Stone*. This query performs to extract the distinct Customer_ID and Customer_Name of all customers associated with this artist. The outcome, displayed in Fig. 6**,** confirmed that exactly 47 distinct customers are engaged with '*The Rolling Stones'* that confirms the authenticity and reliability of the customer reach measure.

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Customer_ID	Customer_Name	Customer_	Customer_Name
Cust02	Leonie KÃ¶hler	Cust33	Ellie Sullivan
Cust03	FranÃ§ois Tremblay	Cust34	JoÃ£o Fernandes
Cust04	BjÃ¸rn Hansen	Cust35	Madalena Sampaio
Cust05	FrantiÅ¡ek WichterlovÃ¡	Cust36	Hannah Schneider
Cust06	Helena HolÃ½	Cust38	Niklas SchrÃ¶der
Cust07	Astrid Gruber	Cust39	Camille Bernard
Cust09	Kara Nielsen	Cust40	Dominique Lefebvre
Cust10	Eduardo Martins	Cust41	Marc Dubois
Cust11	Alexandre Rocha	Cust42	Wyatt Girard
Cust13	Fernanda Ramos	Cust43	Isabelle Mercier
Cust14	Mark Philips	Cust45	Ladislav KovÃ¡cs
Cust15	Jennifer Peterson	Cust46	Hugh O Reilly
Cust17	Jack Smith	Cust47	Lucas Mancini
Cust19	Tim Goyer	Cust48	Johannes Van der Berg
Cust20	Dan Miller	Cust50	Enrique MuÃ±oz
Cust21	Kathy Chase	Cust51	Joakim Johansson
Cust23	John Gordon	Cust52	Emma Jones
Cust24	Frank Ralston	Cust54	Steve Murray
Cust25	Victor Stevens	Cust55	Mark Taylor
Cust26	Richard Cunningham	Cust56	Diego GutiÃ©rrez
Cust27	Patrick Gray	Cust57	Luis Rojas
Cust30	Edward Francis	Cust58	Manoj Pareek
Cust31	Martha Silk	Cust59	Rishabh Mishra
Cust32	Aaron Mitchell		

Figure 5: Customer Count Result of 'The Rolling Stones' on MuDW Data Warehouse

II) Determining Artist performance based on total bill amount

This section measures the total performance of each artist in terms of commercial performance based on the derived measure total bill amount, which is calculated as (Discounted_Unit_Price * Track_Quantity). It is also quite powerful in determining how much revenue the artists contribute, which serves as good source of measuring their relative performance and popularity.

MDX Query: 2

```
SELECT
    NON EMPTY {[Measures].[Total Bill Amount]} ON COLUMNS,
    NON EMPTY {
            ([Dim Artist Album].[Artist Name].[Artist Name].ALLMEMBERS *
             [Dim Artist Album].[Artist ID].[Artist ID].ALLMEMBERS *
             [Dim Artist Album].[Performer].[Performer].ALLMEMBERS)
        } ON ROWS
    FROM [MUSIC_CUBE];
```

The above MDX query calculates the *Total _Bill_Amount* per artist using transactional revenue calculated on customer purchases so that the economic performance of each is comparatively evaluated. This enables performance evaluation by revenue in OLAP environment by retrieving artist name, artist id, and performer details.

Artist Name	Artist ID	Performer	Total Bill Amount
Queen	A51	Band	190.08
Jimi Hendrix	A94	Artist	185.13
Nirvana	A110	Band	128.7
Red Hot Chili	A127	Band	128.7
Pearl Jam	A118	Band	127.71
AC/DC	A01	Band	122.76
Guns N Rose:	A88	Band	122.76
Foo Fighters	A84	Band	119.79
The Rolling St	A142	Band	115.83
Metallica	A50	Band	104.94

Figure 6: Top 10 Revenue-Generating Artists Based on Total Bill Amount

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Figure 6 reveals the result of the query with only the Top 10 highest revenue-generating artists, as per the calculated measure total bill amount, which shows their commercial influence and customer buying pattern. The other records are also represented in the dataset, but are not shown in this output due to ease of analysis Queen became the leading artist (190.08), then Jimi Hendrix (185.13), Nirvana (128.7), and Red Hot Chili (128.7) with high levels of listener engagement and sales. Such insights can help in the strategic assessment of OLAP and improve the market prediction, assessment of artist performances and predictive trend assessment throughout the music business sphere.

III) Artist Performance Analysis through Track Quantity Purchased

In this section, the number of tracks that customers have purchased of each artist is assessed, which is an indicator of the popularity of the artist, customer interaction, and business achievement. The relative performance and level of demand of each artist in the market appeal is determined by a higher purchase volume.

MDX Query: 3

```
SELECT
      NON EMPTY {[Measures].[Track Quantity]} ON COLUMNS,
      NON EMPTY {
              ([Dim Artist Album].[Artist Name].[Artist Name].ALLMEMBERS *
               [Dim Artist Album].[Artist ID].[Artist ID].ALLMEMBERS *
               [Dim Artist Album].[Performer].[Performer].ALLMEMBERS)
      } ON ROWS
FROM [MUSIC_CUBE];
```

The above MDX query calculates the number of tracks bought on each artist, using the measure of track quantity, and associates it with the attributes of the artist, Artists Name, Artist ID and the type of performer. It efficiently examined the amount of tracks bought per artist by this organized querying system, which provides multidimensional performance analysis through customer buying patterns and enables to purchase-based popularity analysis.

Artist Name	Artist ID	Performer	Track Quantity
Queen	A51	Band	192
Jimi Hendrix	A94	Artist	187
Nirvana	A110	Band	130
Red Hot Chili Peppers	A127	Band	130
Pearl Jam	A118	Band	129
AC/DC	A01	Band	124
Guns N Roses	A88	Band	124
Foo Fighters	A84	Band	121
The Rolling Stones	A142	Band	117
Metallica	A50	Band	106

Figure 7: Top 10 Artists Ranked by Purchased Track Quantity

Figure 7 shows the results of the query with only top 10 artists with the highest number of track purchased based on the *Track_Quantity* measure, which shows their popularity depending on the customer purchasing behavior. Queen is on the top of the list with 192 purchased tracks, then in the second place, there is Jimi Hendrix (187), then Nirvana (130), Red Hot Chili Peppers (130), which suggest high market demand and customer interests. These results highlight the popularity of artists on purchasing basis, whereas the lower-ranked artists are also present in the dataset but intentionally left aside to focus the analytical attention on the most influential artists.

IV) OLAP-Based Year-Country Wise Analysis of Top Performer by Total Bill Amount

In order to determine the most popular performer in various countries in each year between 2017 and 2020, the MDX query is executed on MUSIC_CUBE created in Visual Studio. The query uses the TOPCOUNT and GENERATE functions on the Dim_Date, Dim_Artist_Album, and Dim_Location dimensions to identify the most populating performer in each country per year on the basis of the Total_ Bill_Amount measure. The MDX query allows a multidimensional analysis to display the country-wise

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consumer preference in the trend of digital music, and its result is shown in Figure 8 to indicate the best performing performer within each country-year combination.

MDX Query: 4

```
SELECT
        NON EMPTY{ [Measures].[Total Bill Amount] } ON COLUMNS,
        NON EMPTY
             {
                 GENERATE(
                     [Dim Date].[Billing Year].[Billing Year].MEMBERS,
                         TOPCOUNT(
                              (
                              [Dim Date].[Billing Year].CURRENTMEMBER *
                              [Dim Location].[Billing Country].[Billing Country].MEMBERS *
                              [Dim Artist Album].[Performer].[Performer].MEMBERS
                              ), 1, [Measures].[Total Bill Amount]))
              } ON ROWS
FROM [MUSIC_CUBE]
```

Billing Year	Billing Country	Performer	Total Bill Amount
2017	USA	Band	188.1
2018	USA	Band	203.94
2019	USA	Band	211.86
2020	USA	Band	203.94

Figure 8: Year-countrywise Topper forming Performer based on Total Bill Amount

V) OLAP-Based Genre Trend Analysis

The genre-wise analysis used an MDX query to determine the most revenue-generating music genre in a given year between 2017 and 2020. The query processes the highest revenue-making genre by each year- country by querying across the Dim_ Date, Dim_Location and Dim_Track dimensions of the MUSIC_CUBE on *Total_Bill_Amount* measure. The resulting output, as shown in Figure 9, indicates varying consumer preferences and genre-specific tastes in various regions and can guide music platforms and stakeholders to make well-informed strategic decisions.

MDX Query: 5

```
SELECT
        NON EMPTY{ [Measures].[Total Bill Amount] } ON COLUMNS,
        NON EMPTY
             {
        GENERATE(
                        [Dim Date].[Billing Year].[Billing Year].MEMBERS,
        TOPCOUNT(
                         (
                           [Dim Date].[Billing Year].CURRENTMEMBER *
                           [Dim Location].[Billing Country].[Billing Country].MEMBERS *
                           [Dim Track].[Genre Name].[Genre Name].MEMBERS
                        ), 1,[Measures].[Total Bill Amount]
        ) )
        } ON ROWS
FROM [MUSIC_CUBE]
```


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Billing Year	Billing Country	Genre Name	Total Bill Amount
2017	Canada	Rock	141.57
2018	USA	Rock	131.67
2019	USA	Rock	132.66
2020	USA	Rock	150.48

Figure 9: Year-countrywise Topper forming Genre based on Total Bill Amount

Multi-Criteria Artist Ranking

The computed C_i for each artist is shown in Table 2.

Table 2: Computed C_i values

Artist_ID	Performer	*Ci*
A001	Band	0.66
A002	Band	0.06
A003	Band	0.44
A004	Artist	0.40
A005	Band	0.34
A006	Artist	0.10
A007	Band	0.23
A008	Group	0.34
A010	Artist	0.02
A011	Band	0.09
A012	Band	0.39
A013	Band	0.01
A014	Artist	0.02
A015	Artist	0.13
A016	Artist	0.07
A017	Artist	0.07
A018	Band	0.01
A019	Band	0.01
A022	Band	0.41
A024	Artist	0.00
A027	Artist	0.06
A036	Band	0.10
A037	Artist	0.04
A042	Artist	0.03
A046	Artist	0.03
A050	Band	0.57
A051	Band	0.98
A052	Band	0.34
A053	Band	0.05
A054	Band	0.57
A055	Artist	0.01
A056	Artist	0.01
A057	Band	0.15
A058	Band	0.30
A059	Band	0.18
A068	Artist	0.39
A072	Artist	0.02
A076	Band	0.31
A077	Artist	0.02
A078	Band	0.18
A080	Artist	0.02
A081	Artist	0.51
A082	Band	0.15
A083	Band	0.00
A084	Band	0.65
A085	Artist	0.41
A086	Band	0.01
A087	Band	0.51
A088	Band	0.66
A089	Band	0.04
A090	Band	0.46
A091	Artist	0.28
A092	Band	0.35
A093	Band	0.48
A094	Artist	0.93
A095	Artist	0.06
A096	Band	0.09
A098	Band	0.19
A099	Band	0.05
A100	Artist	0.22
A101	Artist	0.04
A102	Band	0.09
A103	Artist	0.24
A104	Band	0.29
A105	Band	0.11
A106	Band	0.28
A109	Band	0.10
A110	Band	0.69
A112	Group	0.00
A113	Band	0.00
A114	Artist	0.20
A115	Band	0.02
A116	Artist	0.02
A118	Band	0.68
A120	Band	0.39
A121	Band	0.01
A124	Band	0.56
A125	Band	0.05
A126	Artist	0.03
A127	Band	0.69
A128	Band	0.22
A130	Band	0.10
A132	Band	0.29
A134	Band	0.24
A135	Band	0.51
A137	Band	0.06
A138	Band	0.40
A139	Band	0.29
A140	Band	0.46
A141	Band	0.44
A142	Band	0.63
A144	Band	0.42
A145	Band	0.05
A146	Band	0.02
A147	Band	0.00
A149	Band	0.01
A150	Band	0.50
A151	Band	0.14
A152	Band	0.51
A153	Group	0.16
A155	Artist	0.02
A157	Band	0.00
A179	Band	0.40
A180	Group	0.16
A196	Band	0.22
A197	Band	0.02
A199	Artist	0.02
A200	Band	0.04
A201	Artist	0.02
A202	Artist	0.02
A203	Artist	0.02
A204	Band	0.07
A205	Artist	0.26
A211	Artist	0.00
A212	Artist	0.03
A213	Band	0.00
A214	Group	0.00
A227	Artist	0.05
A236	Artist	0.00
A238	Artist	0.01
A240	Artist	0.05
A247	Group	0.00
A248	Group	0.00
A250	Artist	0.02
A252	Artist	0.52
A253	Band	0.07
A255	Artist	0.00
A259	Group	0.00
A268	Artist	0.05
A272	Group	0.01

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Table 3: Top rated artists

Artist Name	Ranked Ci
Queen	0.976838
Jimi Hendrix	0.932449
Nirvana	0.690351
Red Hot Chili Peppers	0.686303
Pearl Jam	0.682519
AC/DC	0.659188
Guns N Roses	0.659188
Foo Fighters	0.646669
The Rolling Stones	0.630283
Metallica	0.572472

Table 2 emphasizes the TOPSIS ranking of the best performing artists according to three major criteria namely: *Customer Reach*, *Total_Bill_Amount*, and total *Track_Quantity* sold. The higher Ci values represent better overall performance and this means they have better multi-dimensional impact in both customer-engagement and commercial measures.

VI. RESULTS AND DISCUSSION

1. Final Ranking of Artists

In the study, an integrated framework OLAP-TOPSIS is effectively applied to analyze artist rank through multidimensional data extracted in the data warehouse. Firstly, MDX query formulations, which are used in the section 5(A-C), are implemented in SQL Server Analysis Services to retrieve aggregated measurements, like *Customer Reach*, *Total_Bill_Amount* and total *Track_Quantity* sold by each artist in multiple years. These query results (Figures 4, 6, and 7) served as the decision matrix for the application of the TOPSIS method, considering these criterions. Using normalized decision matrices, ideal and negative-ideal solutions are identified. The Euclidean distance of each artist from these reference points is computed to determine the relative closeness coefficient.

Thereafter, artists are ranked based on how well they performed those with higher closeness coefficients are ranked higher. Table 2 displays the top 10 artists according to their performance metrics, which is the final ranking result generated by the TOPSIS method. The OLAP analysis enabled through MDX provides a conceptual foundation for understanding the TOPSIS outcomes summarized in Table 2. The graphical representation of the TOPSIS-based ranking results regarding various performance criteria is presented in Figure 10. The visualization makes it very clear that artists like Queen and Jimi Hendrix are more prominent as the higher C_i values prove their high rank in the multidimensional evaluation model.

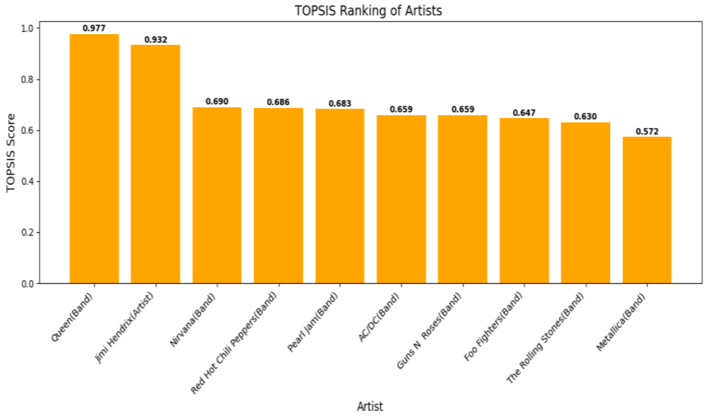

Figure 10: TOPSIS-based Top 10 Artists

Finally, the combination of OLAP-based querying, TOPSIS ranking, and Python-based visualizations provided a multidimensional data-driven analysis of music trends and artist popularity.

2. Year-country wise Top performing Performer based on Total Bill Amount

OLAP-based multidimensional analysis is conducted to analyse the performer-wise and country-wise revenue trends. The visualization of the OLAP cube in Fig. 10 indicates clearly the correlation between the three different categories of performers (Artist, Band, and Group) where the band always achieved the highest *Total_Bill_Amount* in each year between 2017 and 2020. This shows that band performances are the most commercially successful and have continued to be the highest revenue contributor annually. Similarly, the consolidated visualization also shows the country-based revenue distribution with the USA generating the most revenue in all years, thus making it the most robust market to conduct band performances. The total outcomes of these

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findings prove that Band is the favorite type of performer, and USA is the top consumer market between the 2017 and 2020. The integrated figure shows that OLAP cube analysis can be used to comprehend the sales trends over time, the popularity of performers, and the market dominance by geographic areas to make strategic business decisions.

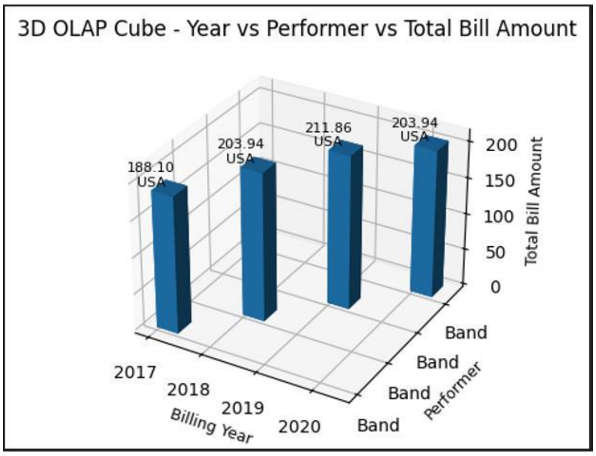

Figure 11: Year-wise and Country-wise Revenue Distribution by Performer using OLAP Cube Visualization

3. Year-country wise Top performing Genre based on Total Bill Amount

The multidimensional analysis based on OLAP is conducted to analyze the genre-based and country-based revenue trends. As shown in Fig. 10, Rock genre has the highest *Total_Bill_Amount* every year between 2017 and 2020, indicating its persistent commercial appeal. The visualization also emphasizes the USA as the largest revenue maker country of rock music during the period. These findings verify that rock is the most profitable genre and USA the biggest revenue center. The visualization shows how OLAP cube analysis can capture year-over-year dynamics in sales, genre popularity and geographic market dominance to analyze it strategically.

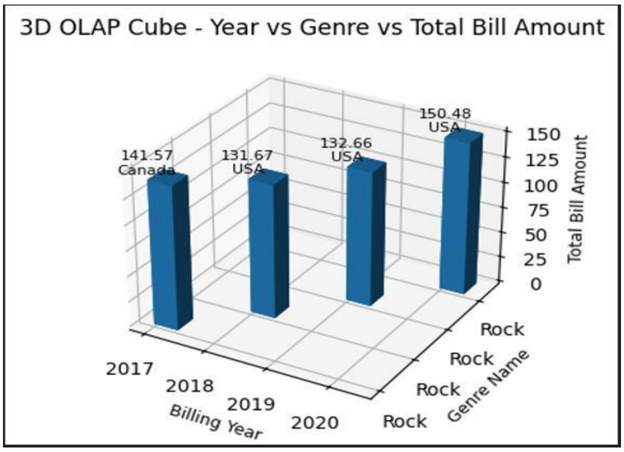

Figure 12: Year-wise Top Music Genre Based on Total Invoice

VII. CONCLUDING REMARKS

This study provides a multi-criteria decision-making and multidimensional data analysis-based structure that would be used to assess and visualize the performance of artists. The TOPSIS method is successfully used to rank the artists using three vital parameters Customer Reach, *Total_Bill_Amount* and total *Track_Quantity* sold. The MDX queries are used to derive these metrics, while ETL processes are employed to clean and handle missing values. Combining the data warehouse with TOPSIS methodology allowed the efficient and objective use of the consolidated multidimensional data in creating transparent and reproducible rankings, thus enhancing the computational performance and scalability of the techniques to larger scale datasets.

The TOPSIS scoring is used to identify the top 10 artists, which is then visualized in Python to improve their interpretability. Moreover, 3D OLAP cubes are created in the fig. 11 and fig. 12 to emphasize the performance trends by time and location based on the MDX queries. The OLAP analysis (in the form of multi-dimensions) of the performer-wise and genre-wise revenue trends indicates a pattern of consistent dominance of bands and the rock genre in all years between 2017 and 2020. In both results, USA is the highest revenue generating country with the highest *Total_Bill_Amount* and this implies strong listener engagements. These findings represent the overall market pattern, with certain types of performers and genres repeatedly outperforming others both in time and geographic scale. In general, the findings indicate that OLAP cube analysis is effective in identifying the key drivers of revenue to be used in strategic decision-making.

The system can be expanded in the future with the addition of recommender systems as well as data mining algorithms like FP-Growth and market basket analysis to detect common patterns and enhance personalized recommendation in the music field.

REFERENCES

[1] Patel, S. (2021). Data warehousing fundamentals: A comprehensive study. *ResearchGate*. https://www.researchgate.net/publication/354680771

[2] Nambiar, A., & Mundra, D. (2022). An overview of data warehouse and Data Lake in modern enterprise data management. *Information*, 6(4), 132. https://www.mdpi.com/2504-2289/6/4/132

[3] De Witte, M., Pinho, A. D. S., Stams, G. J., Moonen, X., Bos, A. E., & Van Hooren, S. (2022). Music therapy for stress reduction: a systematic review and meta-analysis. *Health psychology review*, 16(1), 134-159.

ISSN (online): 2581-3048
Volume 10, Issue 1, pp 1-19, January-2026
https://doi.org/10.47001/IRJIET/2026.101001

[4] Nwokenna, E. N., Sewagegn, A. A., & Falade, T. A. (2022). Effect of educational music intervention on emotion regulation skills of first-year university music education students. *Medicine*, 101(47), e32041.

[5] Feng, Y., & Wang, M. (2025). Effect of music therapy on emotional resilience, well-being, and employability: a quantitative investigation of mediation and moderation. *BMC psychology*, 13(1), 47.

[6] Li, M., & Zhang, L. (2025). Research on the optimisation of music education curriculum content and implementation path based on big data analysis. *Applied Mathematics & Nonlinear Sciences*, 10(1).

[7] Wang, X., & Wang, T. (2023). Construction and application of a big data analysis platform for college music education for college students' mental health. *International Journal of Data Warehousing and Mining (IJDWM)*, 19(4), 1–16.

[8] Aasim, S. (2024). Harmonizing sleep: Exploring the multifaceted role of music therapy in sleep health. *Chemotherapy*, 24(3), 360-369.

[9] Chatterjee, D. (2024). The Role of Music Therapy in Stress Reduction. *International Journal for Multidisciplinary Research (IJFMR)*, 6(2).

[10] Abrarov, R. D., & Khudaybergenov, T. A. (2024, November). Using OLAP Cubes as Dataset for Neural Networks: Integrating Business Intelligence and Artificial Intelligence. *In 2024 IEEE 3rd International Conference on Problems of Informatics, Electronics and Radio Engineering (PIERE)* (pp. 1600-1604). *IEEE*.

[11] Ahmadi, S. (2023). Optimizing data warehousing performance through machine learning algorithms in the cloud. *International Journal of Science and Research*, 12(12), 1859–1867.

[12] Szabat Fernández, A. (2024). Diseño de un almacén de datos para análisis de gustos y hábitos musicales.

[13] Lado Río, C. (2024). Perfil completo de artistas musicais: integrando información de Spotify e MusicBrainz.

[14] Bouaziz, S., Nabli, A., & Gargouri, F. (2021). Towards data warehouse from open data: Case of COVID-19. *International Journal of Hybrid Intelligent Systems*, 17(3-4), 129-142.

[15] Padron-Uy, J., Parihar, A., Gagnier, K., Hains, G., & Wong, A. (2025). Scaling a data warehouse system with machine learning integration for stock market forecasting. *Authorea Preprints*.

[16] Martinez-Mosquera, D., Navarrete, R., Luján-Mora, S., Recalde, L., & Andrade-Cabrera, A. (2024). Integrating OLAP with NoSQL databases in big data environments: Systematic mapping. *Big Data and Cognitive Computing*, 8(6), 64.

[17] Bouaziz, S., Boukettaya, S., Nabli, A., & Gargouri, F. (2025). A formal algebra for document-oriented NoSQL data warehouses: formalisation and evaluation. *Cluster Computing*, 28(3), 170.

[18] Fan, X., & Lu, J. (2024). Enterprise-level data warehouse system based on Hive in big data environment. *Procedia Computer Science*, 243, 67–75.

[19] Djiroun, R., Guessoum, M. A., & Benkhelifa, E. H. (2024, December). An OLAP internal/external cube recommendation approach based on artificial intelligence techniques. *In Global Congress on Emerging Technologies (GCET-2024)* (pp. 145–152). IEEE.

[20] Kumar, N., Kushwah, G., & Singh, P. (2025). Developing a music data warehouse for determining audience preferences. *In Progressive Computational Intelligence, Information Technology and Networking* (pp. 217-223). *CRC Press*.

[21] Rana, M. (2025). Overview of data warehouse architecture, big data and green computing.

[22] Kimball, R., & Ross, M. (2010). The Kimball group reader: relentlessly practical tools for data warehousing and business intelligence. *John Wiley & Sons*.

[23] Lyu, S., Craig, S., O'Reilly, G., & Taniar, D. (2025). The development and use of data warehousing in clinical settings: a scoping review. *Frontiers in Digital Health*, 7, 1599514.

[24] Chilukoori, S. S. R., Gangarapu, S., & Kadiyala, C. K. DATA WAREHOUSING IN THE FINANCIAL SERVICES INDUSTRY: CHALLENGES, OPPORTUNITIES, AND REGULATORY CONSIDERATIONS.

[25] Maaitah, T. (2023). The Role of Business Intelligence Tools in the Decision Making Process and Performance. *Journal of intelligence studies in business*, 13(1).

[26] Güneş, İ., & Birgin, M. K. (2023). Implementing data warehouse infrastructure for an e-learning system. *Gümüşhane Üniversitesi Fen Bilimleri Dergisi,* 13(3), 750-766.

[27] Yadav, U., Bhandari, H. L., & Poudel, S. Implementation of Data Warehouse Technology in Academic Data Management.

[28] Sanjeetha, M. B. F., & Asanka, D. (2025). Design and Implementation of Data Warehousing for Small and Medium Sized Enterprises (SMEs): A Cost-Effective Approach in Online Stores. *Asian Journal of Computer Science and Technology*, 14(1), 57-65.

[29] Navarro, J., Gaujoux, V., Ouimet, M. C., Ferreri, L., & Reynaud, E. (2023). How does background music affect drivers' behaviours, emotions and mood behind

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the wheel?. *Transportation research part F: traffic psychology and behaviour*, 98, 47-60.

[30] Xian, X., Zhang, X., Zheng, D., & Wang, Y. (2024). Mental Health Benefits of Listening to Music During COVID-19 Quarantine: Cross-Sectional Study. *JMIR Formative Research*, 8(1), e46497.

[31] Feng, Y., & Wang, M. (2025). Effect of music therapy on emotional resilience, well-being, and employability: a quantitative investigation of mediation and moderation. *BMC psychology*, 13(1), 47.

[32] Yingjie, F., & Mingda, W. (2024). Effect of Music Therapy on Emotional Resilience, Well-Being, and Employability: A Quantitative Investigation of Mediation and Moderation.

[33] Najm, I. A., Dahr, J. M., Hamoud, A. K., Alasady, A. S., Awadh, W. A., Alshawki, M. B., & Humadi, A. M. (2022). OLAP mining with educational data mart to predict students' performance. *Informatica*, 46(5).

[34] Alkhanifer, A., & AlZubi, A. A. (2024). Big data-based query optimization for business intelligence. *Intelligent Data Analysis*, 1088467X251331665.

[35] Lyu, S., Craig, S., O'Reilly, G., & Taniar, D. (2025). The development and use of data warehousing in clinical settings: a scoping review. *Frontiers in Digital Health*, 7, 1599514.

[36] Lv, Y. (2025). Research on the Application of Data Warehouse in Education Evaluation System. *International Journal of Cognitive Informatics and Natural Intelligence (IJCINI)*, 19(1), 1-13.

[37] Cormier, K., Padron-Uy, J., Wong, A., Gagnier, K., & Parihar, A. (2025). Data Warehouse Design for Multiple Source Forest Inventory Management and Image Processing. *arXiv preprint* arXiv:2502.07015.

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