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Egyptian Chinese University

Faculty of Engineering & Technology

Software Engineering & IT Department

Graduation Project SET497

Final Report

Project Title

|  |
| --- |
| AI-Powered Music Platform |

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Executive Summary (1 page)

A concise summary of the:

* + Project scope,
  + Project objectives briefly.
  + Key findings and outcomes.
  + A brief mention of perceived challenges.
  + Final recommendations and future plans.

Table of Contents

[Executive Summary (1 page) 1](#_Toc185505735)

[Table of Contents 2](#_Toc185505736)

[**1.** **Introduction (2-3 pages)** 3](#_Toc185505737)

[2. Literature Review (3-4 pages) 4](#_Toc185505738)

[2.1. Foundational Approaches in Music Recommendation 4](#_Toc185505739)

[**3.** **Methodology (2-3 pages)** 5](#_Toc185505740)

[4. Project Progress (3-5 pages) 6](#_Toc185505741)

[**5.** **Challenges and Solutions (1–2 pages)** 7](#_Toc185505742)

[6. Future Work (1-2 pages) 8](#_Toc185505743)

[**7.** **Conclusion (1 page)** 9](#_Toc185505744)

[8. References (1-2 pages) 10](#_Toc185505745)

[**9.** **Appendices (As needed)** 11](#_Toc185505746)

# Introduction (2-3 pages)

* Background information about the project.
* Scope of the Project: to provide a comprehensive overview of the project's focus
* Define the problem your project intends to solve.
* Objectives of the project: What the project aims to achieve.
* Importance or relevance of the project to the field.

# Literature Review

Music recommendation systems (MRS) have evolved significantly, becoming a cornerstone of digital music platforms. They help users navigate extensive catalogs, personalize listening experiences, and reduce decision fatigue. This review examines foundational approaches, recent advancements, and the gaps addressed by this project’s AI-powered music platform.

* 1. Review of Academic Foundations

The reviewed academic papers highlight the rapid evolution of music recommendation systems (MRS) and the innovative methodologies addressing their limitations. Hybrid approaches, particularly those leveraging Graph Neural Networks (GNNs), emerge as a critical solution for challenges like data sparsity, popularity bias, and the need for improved diversity and personalization. These models effectively capture complex user-item-content relationships, providing a strong foundation for scalable, graph-driven recommendation systems.

The integration of socially-aware frameworks is another significant advancement, focusing on aligning recommendations with cultural trends and community behaviors. This approach enhances engagement by incorporating timeliness and relevance into recommendations, making systems more adaptable to real-world social dynamics.

Audio feature extraction and classification techniques have also advanced through the use of pre-trained neural networks and clustering methods. However, these studies underscore persistent gaps, such as the semantic gap in representing audio features and the computational challenges of handling large-scale datasets. Addressing these gaps is essential for building multimodal systems that integrate audio, textual, and contextual data effectively.

Additionally, the importance of mitigating cold-start issues and improving scalability is repeatedly emphasized across studies. Techniques like hybrid models, multimodal integration, and clustering provide valuable strategies for overcoming these challenges. These insights collectively inform the design of this project’s AI-powered music platform, focusing on enhancing accuracy, diversity, fairness, and scalability.

* 1. Foundational Approaches
* Collaborative Filtering (CF) :

CF is one of the earliest and most widely adopted techniques in recommendation systems. It relies on user interaction data, such as song plays, ratings, and skips, to identify patterns and make recommendations.

Strengths: CF excels in domains with rich interaction data, enabling it to uncover shared preferences among users. For example, if two users have similar listening histories, CF recommends music enjoyed by one user to the other.

Weaknesses: However, CF suffers from cold-start problems, where it struggles to recommend songs for new users or tracks without prior interactions. Additionally, data sparsity—the limited availability of interaction data for less popular songs—reduces its effectiveness. CF systems also exhibit popularity bias, favoring widely played tracks while neglecting niche music.

* Content-Based Filtering (CBF) :

CBF focuses on the characteristics of the items themselves, such as metadata (artist, genre, album) or extracted audio features (tempo, rhythm, timbre). Recommendations are based on the similarity between a user’s listening history and the features of other tracks.

Strengths: CBF effectively handles the cold-start problem for new users by analyzing music content. It can also recommend lesser-known tracks if their features align with user preferences.

Weaknesses: The method suffers from the semantic gap, where low-level features (e.g., tempo) do not always reflect the user’s perception of music (e.g., mood). Additionally, CBF lacks personalization because it does not consider user interaction data.

* Hybrid Recommendation Systems :

Hybrid systems combine CF and CBF to address their individual limitations. By integrating user interaction patterns and item-specific features, these systems provide better personalization and accuracy. Hybrid approaches are increasingly enhanced with machine learning and deep learning techniques, enabling them to dynamically adapt to diverse user preferences.

* 1. Emerging Trends and Technologies
* Graph Neural Networks (GNNs)

GNNs represent a breakthrough in recommendation systems by modeling users, songs, and their interactions as nodes and edges in a graph. This structure allows GNNs to capture complex relationships and dependencies between entities.

Applications: Models like PinSage have shown exceptional performance in addressing data sparsity and improving recommendation diversity by leveraging graph-based representations of playlists, user interactions, and content features.

Advantages: GNNs enable more accurate and personalized recommendations by incorporating multi-hop relationships (e.g., users connected indirectly through shared playlists).

* Multimodal Integration

Multimodal systems combine various types of data to improve recommendation quality. For example:

Audio Features: Extracted from raw music tracks to capture rhythm, melody, and genre.

Textual Data: Includes lyrics, reviews, and user-generated tags to enrich context.

Visual Content: Such as album art or music videos to capture aesthetic elements.

Contextual Information: Includes user activity logs, location, or time of day to adapt recommendations dynamically.

By integrating these diverse data types, multimodal systems address the semantic gap and provide a richer understanding of user preferences.

* Socially-Aware Frameworks

Socially-aware systems emphasize the communal and cultural aspects of music consumption. These systems:

Leverage playlist sharing and social interactions to identify trends within communities.

Tailor recommendations to align with cultural preferences or group dynamics, enhancing engagement in collectivist societies.

Consider social signals like likes, shares, and co-listening behaviors to improve personalization.

* 1. Common Gaps Across Existing Systems

Existing music apps like Spotify, YouTube Music, Amazon Music, among others have achieved a lot of technologies in the Music Recommendation System, but they have shared several common gaps that limit their effectiveness and inclusivity :

* Popularity Bias: Most systems overly favor mainstream tracks, reducing visibility for niche genres and emerging artists, which impacts diversity and inclusivity.
* Lack of Real-Time Adaptability: Recommendations are often static and fail to account for real-time contextual factors such as user mood, activity, or time of day.
* Limited Personalization for Niche Audiences: While personalization works well for mainstream preferences, these systems struggle to cater to users with eclectic or unique tastes.
* Engagement Over User Satisfaction: Many systems prioritize metrics like clicks and views over meaningful personalization and long-term user satisfaction.
* Scalability Issues: Techniques like manual tagging (e.g., Pandora) or computationally intensive models (e.g., graph-based systems) hinder scalability for platforms with large catalogs and user bases.
* Underutilization of Fairness Metrics: Few systems explicitly address fairness in recommendations, resulting in imbalances that favor popular content over diverse or novel discoveries.

# Methodology (2-3 pages)

* Detailed explanation of the methods used in the project.
* Justification for the chosen methods.
* Any tools, software, programming languages, frameworks or specialized equipment used in the project.
* Overview of the system architecture or design/ diagram.

# Project Progress (3-5 pages)

This section provides a detailed account of the work completed so far in developing our AI-powered music platform. Our progress encompasses research, planning, and early design stages, ensuring a strong foundation for subsequent development phases.

## Phases and Milestones

We have divided our project into several key phases, each with specific tasks and deliverables. The table below summarizes the milestones achieved so far:

|  |  |  |
| --- | --- | --- |
| Phase | Task | Output |
| Research Phase | Conducted literature review of AI-based music classification and recommendation. | Literature review document (Section 2 of this report) |
| Studied existing platforms, AI models, and techniques relevant to the project. |
| Review Paper Submission | Wrote and submitted a review paper on AI in music streaming. | Review paper (under revision for publication). |
| Project Planning Phase | Defined the preliminary scope, requirements, and key features of the project. | Drafted requirement specifications (SRS outline). |
| Design Phase | Designed initial wireframes for the user interface in Figma. | Low-fidelity UI design (Figma prototype). |

## Detailed Account of Progress

### 1. Research Phase

We began by conducting extensive research into the literature surrounding AI-powered music classification, recommendation systems, and natural language processing for music discovery. This phase involved:

Reviewing academic papers and industry articles on AI models like collaborative filtering, content-based filtering, and NLP search techniques.

Analyzing existing music platforms (e.g., Spotify, Pandora) to identify strengths, weaknesses, and gaps that our project can address.

#### Output:

The findings from this research were compiled into a comprehensive Literature Review (Section 2 of this report). This review informs the design and implementation of our AI-powered features.

### 2. Review Paper Submission

To contribute to the field and validate our research approach, we wrote a review paper summarizing current trends and challenges in AI-based music streaming. The paper highlights innovative aspects of our project, such as dynamic classification and personalized metadata enhancements.

#### Output:

The paper was submitted for revision and is currently under review for potential publication.

### 3. Project Planning Phase

We defined the preliminary scope and features of the platform, focusing on three core functionalities:

* Dynamic Classification System: Adaptive music classification based on genre and user preferences.
* Recommendation System: Personalized music recommendations using AI models.
* NLP Search Feature: Context-aware search for intuitive music discovery.

Additionally, we outlined the requirements for each core component and identified key tools and technologies for implementation.

#### Output:

A draft Requirements Specification Document (SRS) is in progress. This document will be refined as the project evolves.

### 4. Design Phase

We initiated the design of the user interface to ensure the platform is user-friendly and visually appealing. This phase included:

* Creating wireframes to visualize user flow and layout.
* Designing low-fidelity prototypes in Figma, covering key screens such as search, recommendations, and user profiles.

#### Output:

A low-fidelity UI prototype in Figma that serves as the foundation for future design iterations.

# Challenges and Solutions (1–2 pages)

* Identification of any obstacles encountered during the project period.
  + Technical Challenges (e.g., implementation difficulties).
  + Organizational Challenges (e.g., time management).
* Explanation of how challenges were addressed or plans to tackle unresolved issues.

# Future Work (1-2 pages)

* Detailed plan for the next phases of the project. A Gantt Chart to illustrate the timeline.
  + A list of main deliverables (e.g., working prototype, documentation).
* Expected outcomes or goals for the next reporting period.

# Conclusion (1 page)

* Recap of the project's current status and future expectations.
* Reinforcement of the project's significance and impact.on the targeted field and potential applications.

# References (1-2 pages)

* Properly formatted list (IEEE) of all sources cited in the report.

# Appendices (As needed)

* Include any additional material that is relevant but not integral to the main text, such as:
  + Detailed tables,
  + extended data sets, or
  + technical drawings.
  + Source code or implementation details.
  + Illustrative diagrams (e.g., system architecture).
  + Testing models (e.g., surveys, evaluation forms).