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Recommendation System For Gaming Preference Analytics

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Abstract: Understanding what players truly prefer remains one of the major challenges in today's gaming industry. Developers often rely on intuition or general market trends rather than structured data, leading to inaccurate targeting and missed opportunities. This research presents a database-driven system for gaming preference analytics, designed to collect, organize, and analyze player activity data such as liked games, playtime, and user interactions. The system applies similarity metrics and data analysis techniques to identify relationships among players and their gaming interests, enabling personalized game recommendations and community insights. The project emphasizes conceptual, logical, and physical database design, ensuring efficient data organization and retrieval. While the core of this work focuses on database development, it also establishes a foundation for future integration of artificial intelligence methods, such as clustering and predictive analytics, to enhance personalization and recommendation accuracy. Overall, this research demonstrates how structured data and analytical modeling can bridge the gap between player behavior and informed decision-making, supporting smarter marketing, improved engagement, and sustainable growth in the gaming industry.

Keywords: Gaming Preference Analytics, Recommendation System, Database Design, Data Analysis, Artificial Intelligence, Predictive Analytics.

INTRODUCTION:

In today's gaming industry, one of the main challenges is understanding what players truly prefer. There is still no well-structured data system that allows developers to clearly identify their audience - what genres they enjoy, how much time they spend playing, or how likely they are to make in-game purchases. As a result, many marketing and design decisions are made based on assumptions rather than real data, often leading to inefficient targeting and missed opportunities.

This project aims to address that problem by designing a database-driven system for gaming preference analytics. The core idea is to collect, organize, and analyze player activity data - such as game ownership, playtime, likes, comments, and interactions - to identify common behavioral patterns. Based on this structured data, the system can recommend games that match a player's interests or suggest similar players with shared preferences.

The solution integrates conceptual, logical, and physical database design with data analysis techniques that measure similarity between users and games. While the foundation of this research is rooted in database management, it also opens opportunities for applying basic AI and machine learning methods -for example, clustering players or predicting preferences - using the stored datasets in the future.

By combining organized data storage with analytical tools, this system provides a foundation for data-driven decision-making in the gaming industry. Developers can gain valuable insights into player behavior, improve their marketing strategies, and enhance player engagement. This research demonstrates how well-structured databases, combined with intelligent analytics, can bridge the gap between raw gaming data and meaningful business insights.

Objective

The main aim of this project is to create a data-based system that helps game developers figure out who their best target audience is. The system will analyze several important factors, such as:

- Which game genres players prefer (like RPGs, FPS, or strategy games).
- How much time players spend on games (casual players vs. hardcore gamers).
- How engaged players are and how long they stick with a game.
- How much money they spend on in-game items or subscriptions.
- Demographic details like age, gender, and location.

By analyzing these different aspects, the system will help developers see patterns in player preferences. With this information, they can improve their marketing campaigns, make better design choices, and even give more personalized recommendations.

The expected result is an advanced system that gathers gaming preference data from multiple sources and delivers insights that developers can actually use. They will be able to access, visualize, and interpret data through a simple dashboard, making it easier to make informed decisions that boost player engagement and overall satisfaction.

Product Perspective and Related Work

Existing research has explored gaming preferences and their relationship with player behavior. The following papers provide insights into these aspects:

- Rathakrishnan et al. (2023) examined the relationship between personality traits and gaming preferences among school students, revealing that certain personality traits cor- relate with a preference for specific game genres [22].
- Zou et al. (2024) investigated how gaming experience influences social behaviors, finding that multiplayer online battle arena (MOBA) games enhance teamwork and collaborative problem-solving skills [30].
- Palma et al. (2022) provided an analytical perspective on the gaming industry using Power BI, highlighting key influencers that affect gaming trends and user engagement [20].
- Yee (2006) identified various motivations for online gameplay that influence player reten- tion [29].
- Park and Doh (2021) applied big data to understand behavioral patterns in MMORPGs [21].
- Drachen et al. (2014) demonstrated how player telemetry data can drive better game design [5].
- Carras et al. (2018) discussed commercial video games as potential therapeutic tools [3].
- Liao et al. (2021) showed how recommendation algorithms improve retention in mobile games [15].
- Hadiji et al. (2014) predicted player churn using real-world datasets [8].
- El Kaliouby et al. (2022) proposed a hybrid recommender system for games [9].
- Thompson et al. (2020) explored psychological metrics to evaluate in-game experiences [23].
- Nacke and Lindley (2010) distinguished playstyle differences between expert and novice players [19].
- Yang and Li (2021) used k-means clustering to segment gamers based on motivation [27].
- Gallagher et al. (2020) proposed retention strategies using player behavior segmentation [6].
- Melhart et al. (2021) profiled gamer personalities across genres [18].
- Xu et al. (2020) developed a multi-source data fusion technique for gamer analytics [26].
- Kim and Kim (2022) investigated how demographic factors affect gaming behavior [10].
- Lee and Kim (2019) analyzed gameplay logs for improving game design through user satisfaction metrics [14].
- Lin et al. (2017) examined the use of analytics in commercial game development [16].
- Weber and Mateas (2011) emphasized player insight through data mining in game design [25].
- Yang et al. (2022) proposed a social-aware contextualized graph neural network for large- scale personalized video game recommendation, improving recommendation accuracy by leveraging social context [28].
- Lee et al. (2022) introduced DraftRec, a personalized draft recommendation system aimed at helping players win in multiplayer online battle arena (MOBA) games [13].
- Wang et al. (2025) developed Prefer2SD, a human-in-the-loop framework balancing sim- ilarity and diversity for in-game friend recommendations [24].
- Dallmann et al. (2022) focused on sequential

item recommendation within the MOBA game Dota 2, applying deep learning methods to predict player needs during gameplay [4].

- Blue et al. (2024) analyzed Steam profiles and reviews to build a game recommendation model, showcasing how user feedback enhances recommendations [2].
- Liu et al. (2022) studied student navigation patterns in game-based learning environments to optimize educational outcomes through analytics [17].
- Kim et al. (2022) discussed frameworks and challenges in applying analytics to game- based learning for education purposes [12].
- Kim and Ifenthaler (2023) explored the validity and generalizability of game-based as-sessments for measuring spatial reasoning skills [11].
- Alonso-Fern´andez et al. (2019) conducted a systematic review of data science applications in game learning analytics, identifying best practices and challenges [1].
- Gauthier et al. (2022) examined the adoption challenges of learning analytics dashboards in game-based learning settings, providing insights into design improvements [7].

METHODS

Data Specification and Sources

1. Entity relationships:

1. USERS – CAN ACT AS – PLAYERS
2. USERS – CAN ACT AS – PUBLISHERS
3. PLAYERS – MUST RECEIVE – RECOMMENDATIONS
4. PLAYERS – GENERATE WITH – PLAYHISTORY
5. PLAYERS – CAN CREATE – PREFERENCES
6. PUBLISHERS – CAN PUBLISH – GAMES
7. GAMES – CREATED BY – PUBLISHERS
8. PREFERENCES – INDICATES – PREFERRED GAMES
9. GAMES – MAY RECEIVE – PREFERENCES
10. GAMES – DESCRIBED BY – TAGS
11. GAMES – BELONG TO – A CATEGORY
12. RECOMMENDATIONS – SUGGEST – GAMES
13. PLAYHISTORY – PLAYED IN – GAMES

2. Relationship sets tables

No	Entity	Explanation	Identity	Attributes	Note	Sample Values	Relationship with
1	USER	Player and Publisher Is-a User.Stores the main user account information.	Strong	Id	Integer	U2212345	PLAYER
				Username	String	Shakhroh	PUBLISHER
				Password	Integer	Pass123456	
				User_type	String	Normal	
				Name	Composite		
				Fname	(String)	Shakhruh	
				Mname	(String)	Poziljon	
				Lname	(String)	Tohirov	
2	PLAYER	Player Is-a User	Strong	Gender	String	Male	USER
				Location	Integer		PREFERENCE
				Email	String	12@mail	PLAY_HISTORY
				Server_region	Integer	Asia	RECOMMENDATION
3	PUBLISHER	Publisher Is-a User	Strong	Website	String	steam com	USER
				Address	String	Tashkent	GAMES
				Phone_number	multivalue	12345	
4	Games	Stores all game details ,Games published by publisher and belong to category ,tags	Strong	Id	String	U12345	PREFERENCE
				Name	String	Shahruh	PLAY_HISTORY
				Age_limitation	Integer	18+	RECOMMENDATION
				Price	Integer	sum 1000	CATEGORY
				Downloads	Integer	1000	TAGS
				Release_date	Integer	25.12.2003	
5	PLAY_HISTORY	Play_history generated by player	Weak	Play_date	Integer	25.12.2024	PLAYER
				Play_duration	Integer	12	GAMES
				Achievements	String	Victory	
6	PREFERENCE	Player creates preference, Preference indicate games	Strong	Id	String	U12345	PLAYER
				Level	Integer	Normal	GAMES
7	RECOMMENDATION	Player receives Recommendation	Weak	Score	Integer	100	PLAYER
				Date	Integer	25.12.2024	GAMES
				Reason	String	Liked	
8	TAGS	Games described by tags	Strong	Id	String	U12345	GAMES
				Name	String	Shakhruh	
9	CATEGORY	Games belong to Category	Strong	Name	String	Action, Adventure	GAMES
				Description	String	Hybrid genre	

Figure 1: Entity Sets

3. Relationship sets tables

No	Relationship	Design Characteristics	Design Values	Note	Sample Values
1	IS-A	Meaning:	A Player Is-a User		
		Type	Is-a		
		Parent Entity Set and Participation (min,max)	Player(1,1)		
		Child Entity Set And Participation (min,max)	User(1,1)		
		Descriptive Attributes	none		
2	IS-A	Meaning:	A Publisher Is-a User		
		Type	Is-a		
		Parent Entity Set and Participation (min,max)	Publisher(1,1)		
		Child Entity Set And Participation (min,max)	User(1,1)		
		Descriptive Attributes	none		
3	GENERATES	Meaning:	Player Generates Play_History		
		Type	Identifying		
		Parent Entity Set and Participation (min,max)	Player(0,N)		
		Child Entity Set And Participation (min,max)	Play_history(1,1)		
		Descriptive Attributes	none		
4	RECEIVES	Meaning:	Player receives Recommendation		
		Type	Identifying		
		Parent Entity Set and Participation (min,max)	Player(0,N)		
		Child Entity Set And Participation (min,max)	Recommendation(1,1)		
		Descriptive Attributes	none		
5	PUBLISH	Meaning:	Publisher Publish Games		
		Type	Identifying		
		Parent Entity Set and Participation (min,max)	Publisher(0,N)		
		Child Entity Set And Participation (min,max)	Games(1,M)		
		Descriptive Attributes	none		
6	PLAYED_IN	Meaning:	Games played in Play_history		
		Type	Non-identifying		
		Parent Entity Set and Participation (min,max)	Games(0,N)		
		Child Entity Set And Participation (min,max)	Play_history(1,1)		
		Descriptive Attributes	none		
7	DESCRIBED_BY.	Meaning:	Games Described by Tags		
		Type	Identifying		
		Parent Entity Set and Participation (min,max)	Games(0,M)		
		Child Entity Set And Participation (min,max)	Tags(0,N)		
		Descriptive Attributes	none		
8	BELONG_TO	Meaning:	Games Belong to Category		
		Type	Non_identifying		
		Parent Entity Set and Participation (min,max)	Games(1,1)		
		Child Entity Set And Participation (min,max)	Category(1,N)		
		Descriptive Attributes	none		
9	SUGGEST	Meaning:	Recommendation suggest Games		
		Type	Identifying		
		Parent Entity Set and Participation (min,max)	Recommendation(1,N)		
		Child Entity Set And Participation (min,max)	Games(1,M)		
		Descriptive Attributes	none		
10	INDICATES	Meaning:	Preference Indicate Games		
		Type	Identifying		
		Parent Entity Set and Participation (min,max)	Preference(0.N)		
		Child Entity Set And Participation (min,max)	Games(0.M)		
		Descriptive Attributes	none		
11	CREATES	Meaning:	Player creates Preference		
		Type	Non-identifying		
		Parent Entity Set and Participation (min,max)	Player(0,M)		
		Child Entity Set And Participation (min,max)	Preference(1,1)		
		Descriptive Attributes	none		

Figure 2: Relationship Sets

Functional Requirements

1. Find the Id and Username of Users who have at least one record in the Play history table.

2. Find the names and IDs of games created by a given publisher.

3. Each time a user finishes playing, insert a new row into PlayHistory with session details.

4. Retrieve games that were preferred by at least 2 users, showing game IDs, names, and count

5. List game titles with their category names for

a specific category

6. Find games tagged with a given tag , showing IDs and names.

7. Compute the average number of Games played per User over a selected period and the distribution of play frequencies.

8. Generate a list of Game recommendations for a user by correlating their Play history and Preferences with similar users' activities.

9. For a given publisher, show total plays and preference counts for each game

10. Identify trends by showing preferences over each month in multiple periods.

Data Design

1. Conceptual Data Design

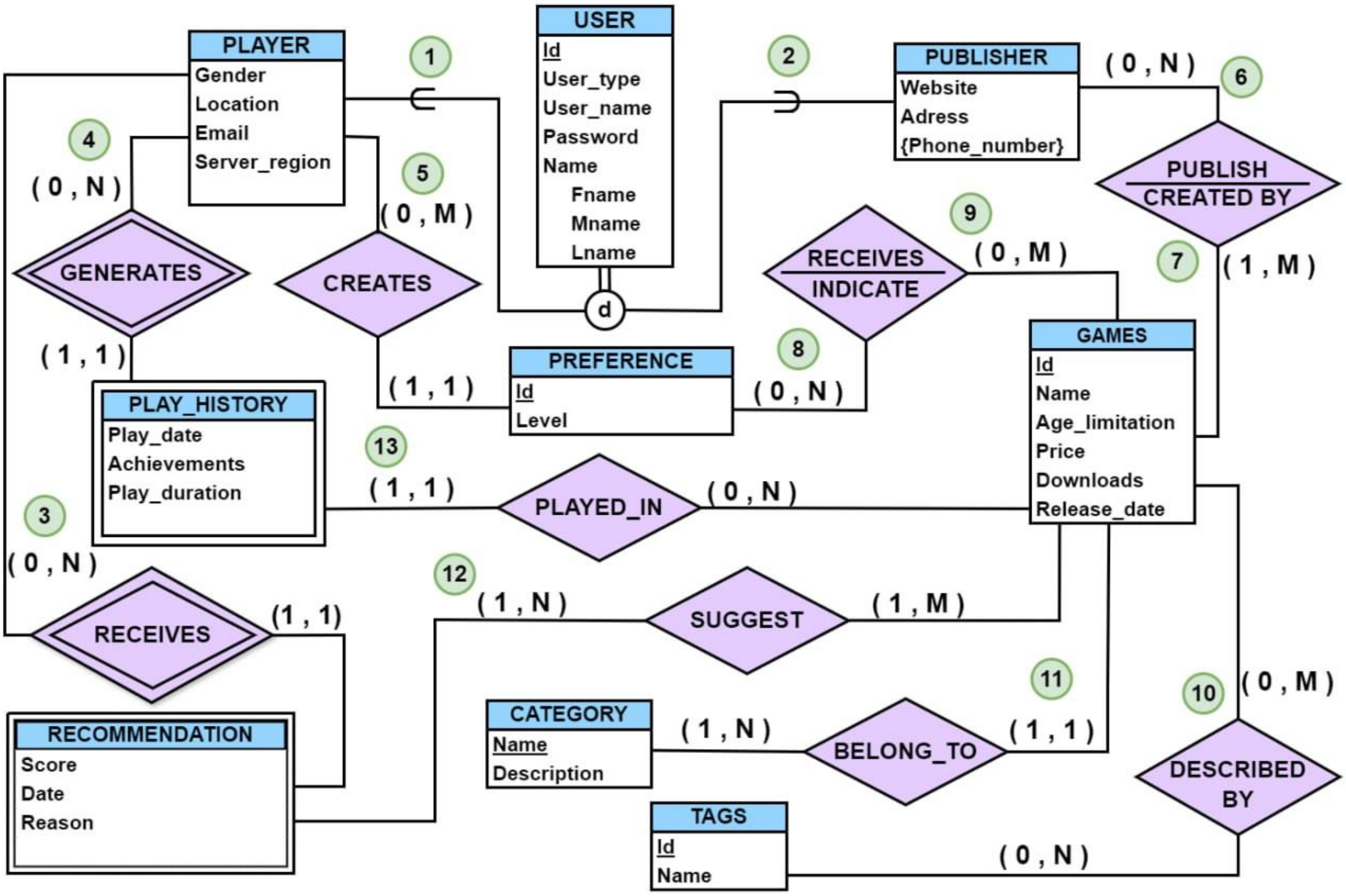


Figure 3: EER DIAGRAM

2. Logical Data Design

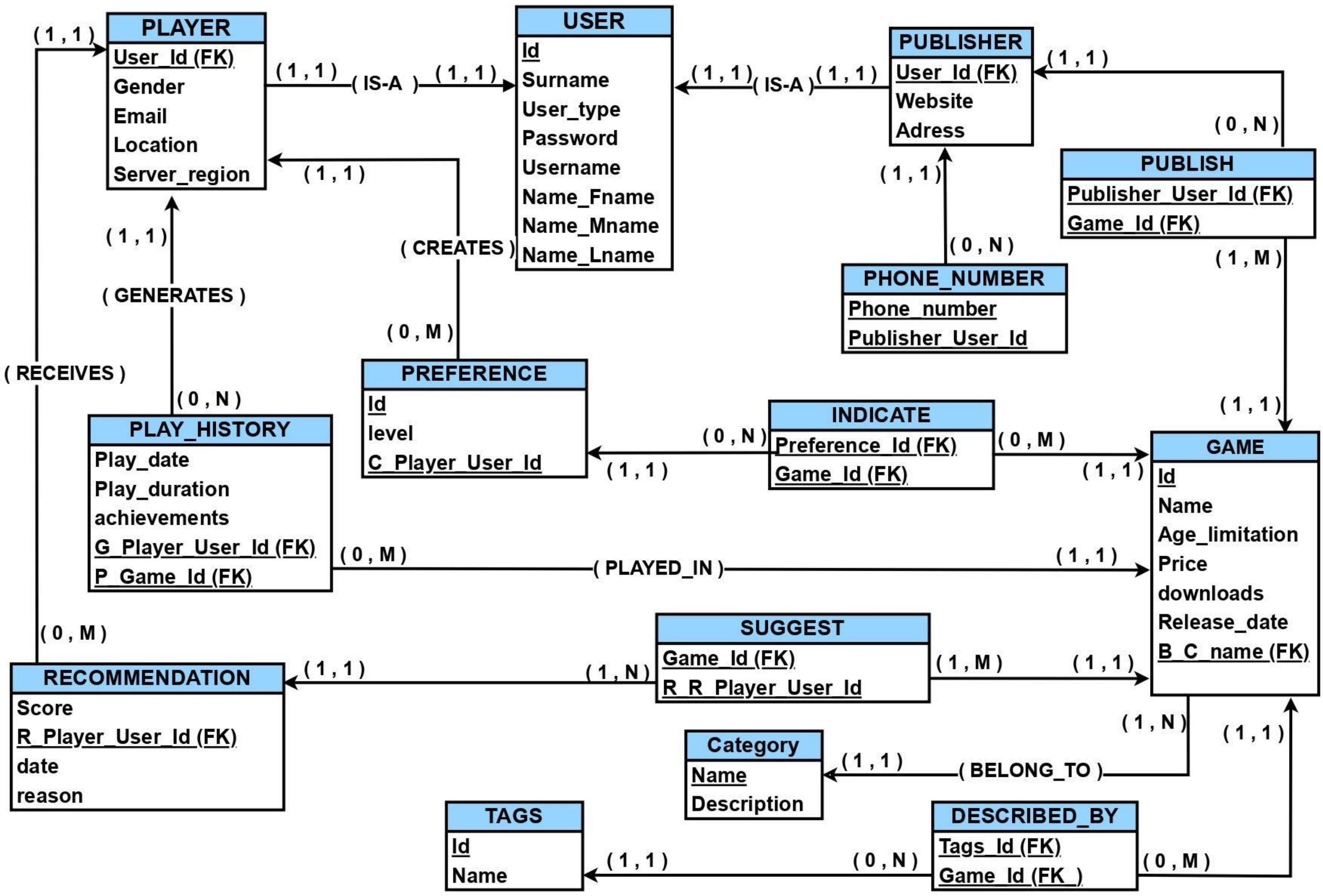


Figure 4: Codd's Model

3. Data Design by MYSQL Workbench

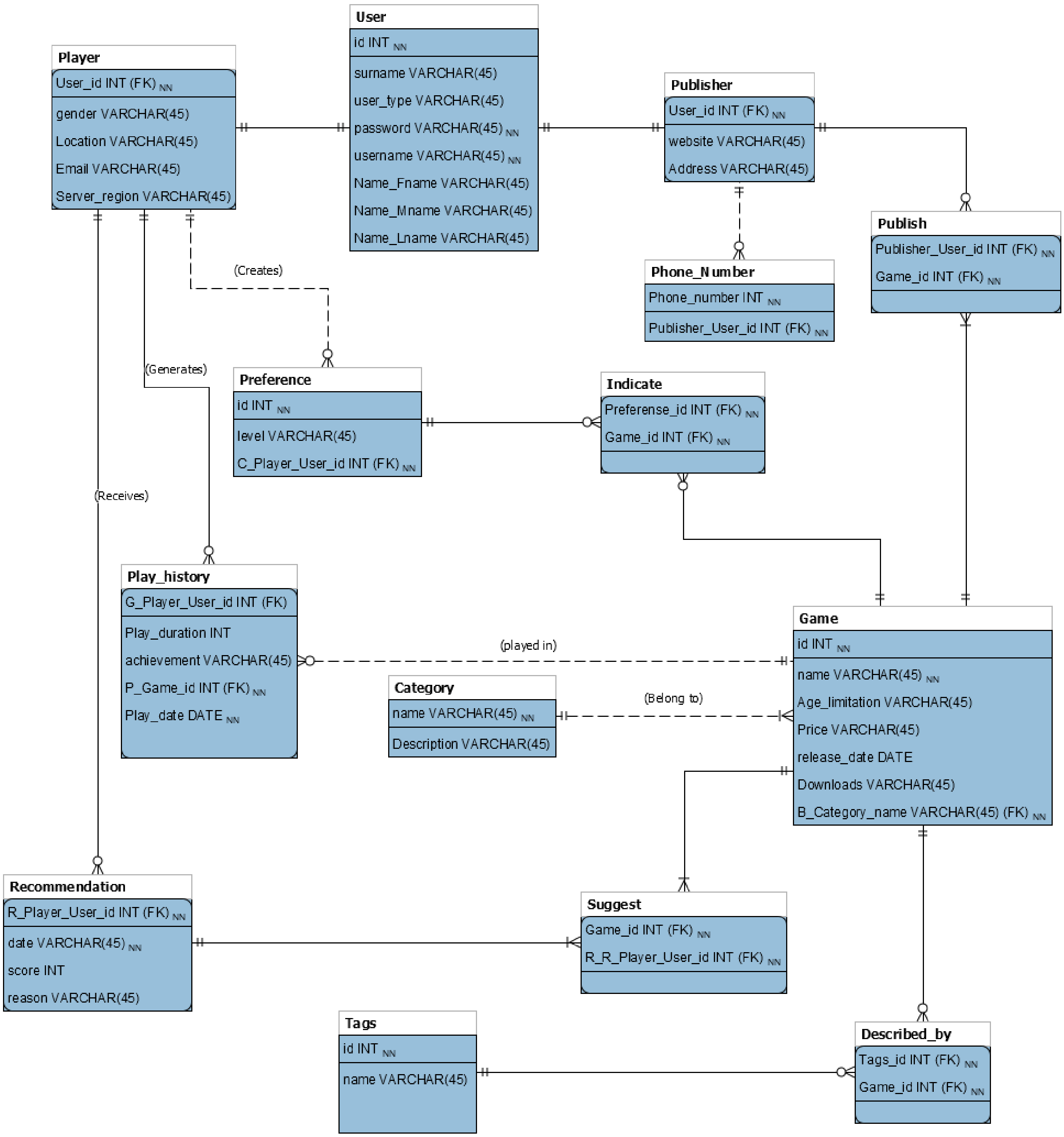


Figure 5: MySQL Workbench Diagram

System Architecture (Block Diagram)

This section introduces the architecture of a game distribution and discovery platform that facilitates both user and publisher interactions. It outlines the authentication flow, account roles, and functionalities available to each role, including game publishing and discovery. Below is the system's block diagram and a detailed explanation of its components.

1. System Architecture Diagram

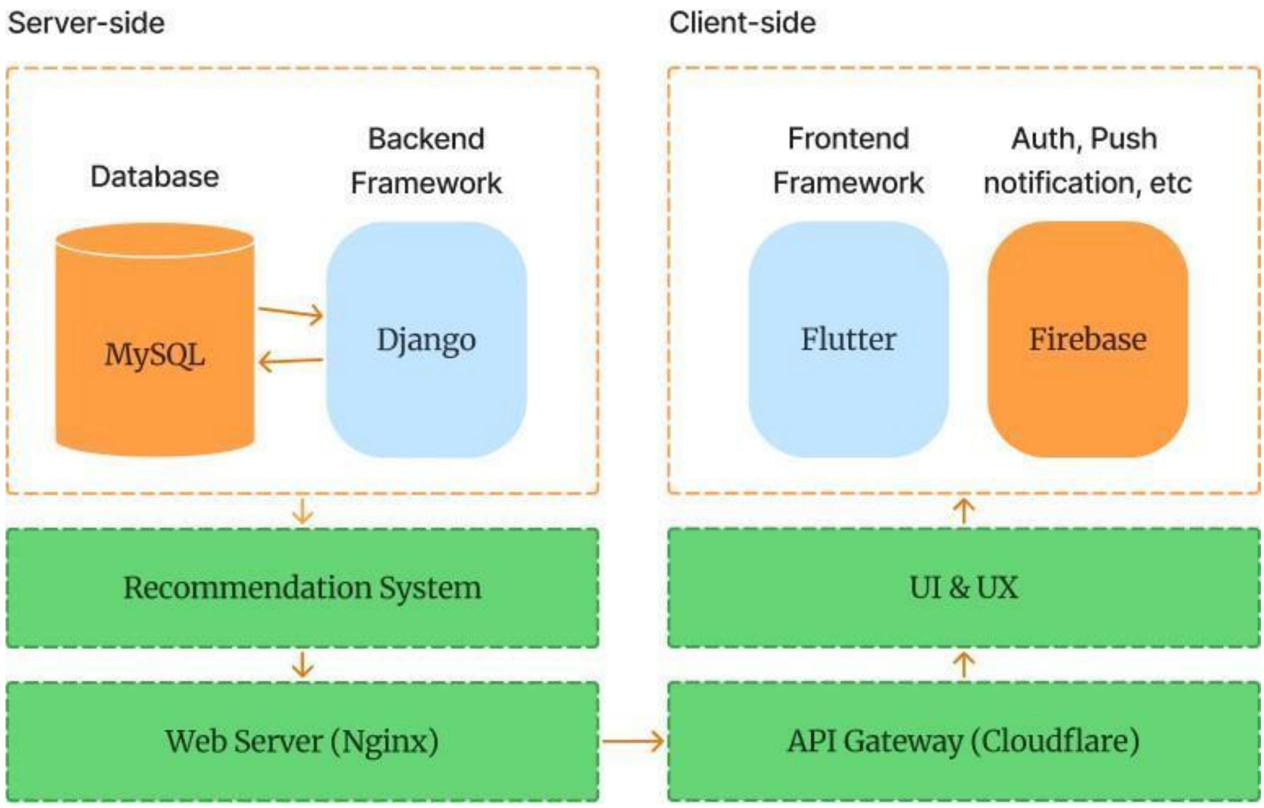


Figure 6: System Architecture Block Diagram

(c) Explanation of System Components

The system architecture consists of several interdependent modules, each contributing to data processing and recommendation delivery:

Server-side

1. Database (MySQL) Functionality:

- Stores structured data (e.g., user data, products, logs, interactions).
- Supports CRUD operations and relationships via SQL.

Designed Algorithms:

- Uses indexing, joins, normalization, and caching for efficient querying.
- May use stored procedures or triggers for automation.

2. Backend Framework (Django) Functionality:

- Acts as the core server-side logic handler.
- Manages routes, APIs, authentication, and business logic.
- Interacts with MySQL to fetch/store data.

Designed Algorithms:

- Implements custom logic (e.g., filtering, validation, transactions).
- May include machine learning integration or REST API pagination.

3. Web Server (Nginx) Functionality:

- Serves static content (HTML, JS, CSS).
- Acts as a reverse proxy to Django applications (via WSGI).
- Load balances requests and ensures high availability.

Designed Algorithms:

- Uses caching, compression, and connection pooling strategies.

4. API Gateway (Cloudflare) Functionality:

- Acts as a protective layer for APIs.
- Handles DNS resolution, SSL termination, rate limiting, and DDoS protection.

Designed Algorithms:

- CDN caching algorithms, Web Application Firewall (WAF) rules.
- Geo-routing and edge computing logic for faster response times.

Client-side

5. Frontend Framework (Flutter) Functionality:

- Builds the UI/UX of the mobile or web app.
- Manages interactions with users and invokes backend APIs.

Designed Algorithms:

- State management (e.g., Provider, Bloc).
- Local caching, lazy loading of content.

6. Firebase (Auth, Push Notifications, etc.) Functionality:

- Manages user authentication (OAuth, email, phone).
- Push notifications for real-time alerts.
- Includes Cloud Messaging, Crashlytics, and Analytics.

Designed Algorithms:

- Token-based authentication.
- Push notification queuing and delivery mechanisms.

Integrated Systems

7. UI & UX Functionality:

- Translates backend responses into visual elements.
- Ensures responsive design and intuitive navigation.

Designed Algorithms:

- A/B testing algorithms.
- User journey mapping and heatmap data integration.

8. Recommendation System Functionality:

- Suggests content or products to users.
- Enhances personalization and engagement.

Designed Algorithms:

- Content-based filtering (based on item features).
- Collaborative filtering (based on user behavior).
- Hybrid models (using both).
- Could use machine learning models like k-NN, SVD, or deep learning.

Experiments and Analysis

This section presents the preliminary testing of the Recommendation System for Gaming Pref- erence Analytics. It contains five representative queries that can be executed on the system's database, reflecting the main use cases. Each query is presented in increasing order of com- plexity and includes:

- A plain English description of the query;
- The corresponding SQL command;
- A screenshot from phpMyAdmin showing the execution and results;
- A screenshot of the system interface that runs the query and displays the output.

1. DDL-DML SQL executed in phpMyAdmin

1. phpMyAdmin Screenshot:

phpMyAdmin Screenshot:

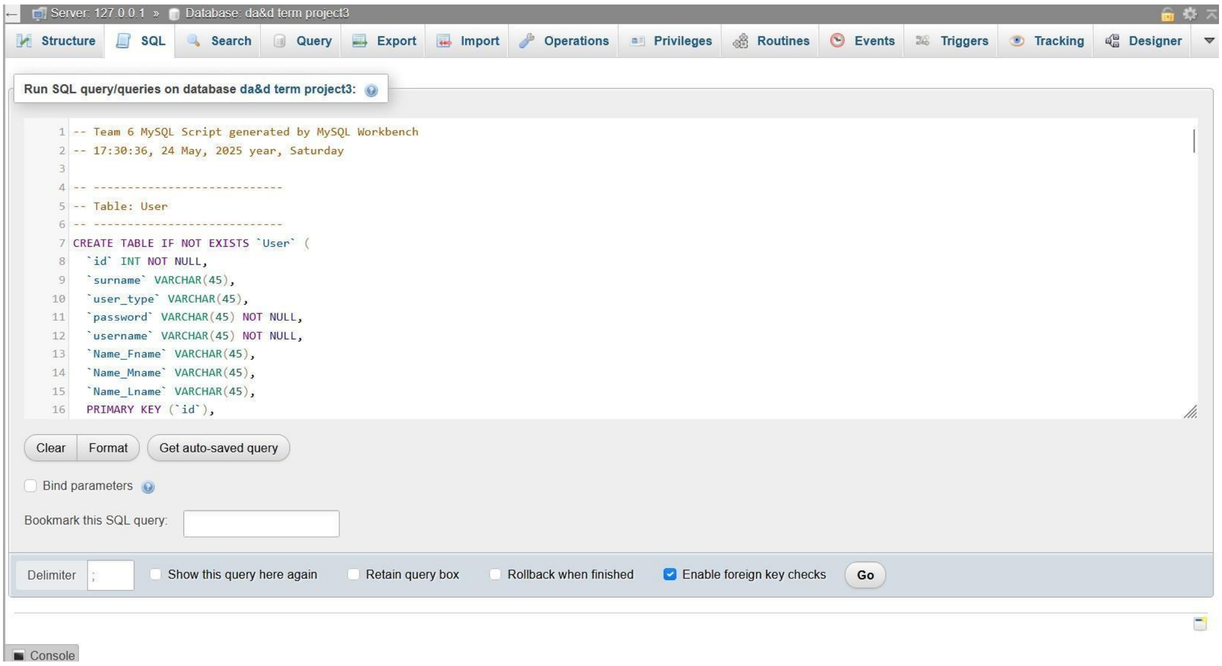


Figure 7: DDL-DML SQL executed in phpMyAdmin on DBMS input

2 phpMyAdmin Screenshot:

Figure 8: DDL-DML SQL executed in phpMyAdmin on DBMS output

Query 1:

1. **Plain English:** Identify trends by showing preferences over each month in multiple periods.
2. **phpMyAdmin Screenshot:**

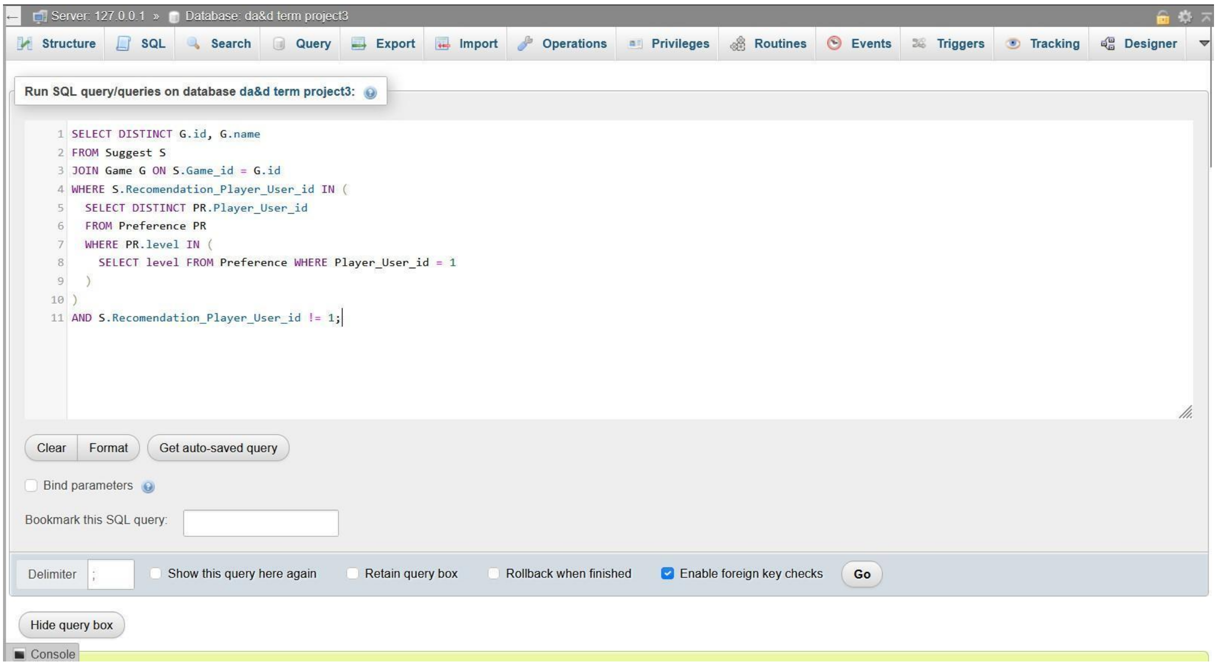


Figure 9: Input of Query 1 executed in phpMyAdmin

2. phpMyAdmin Screenshot:

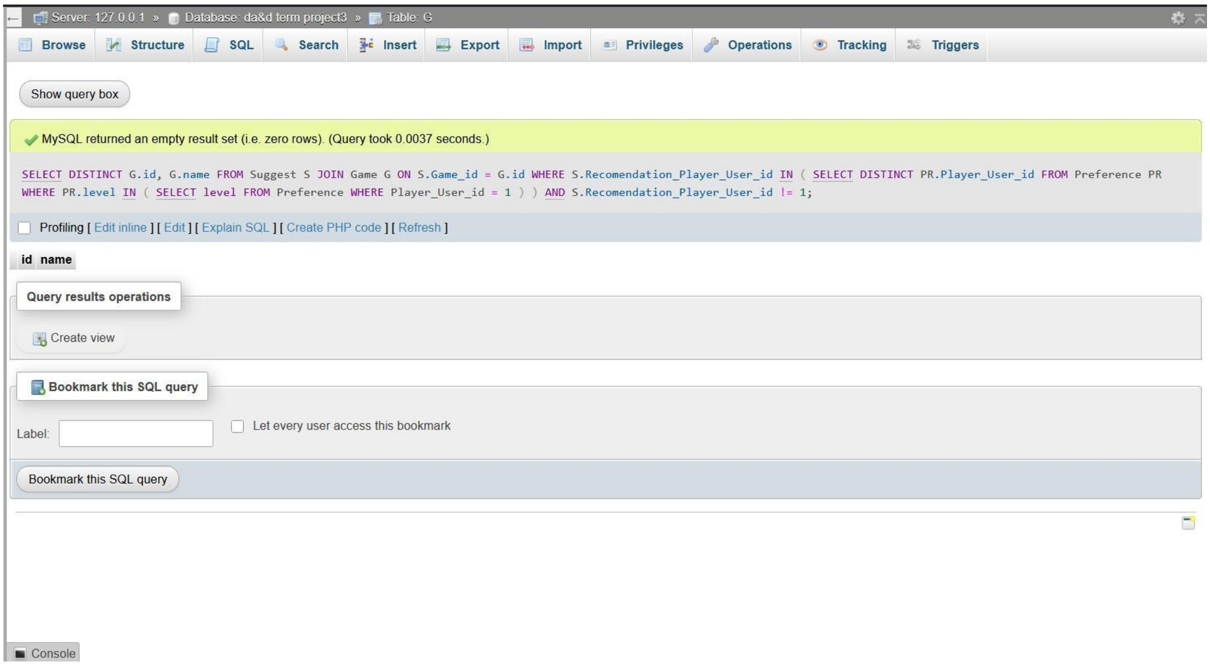
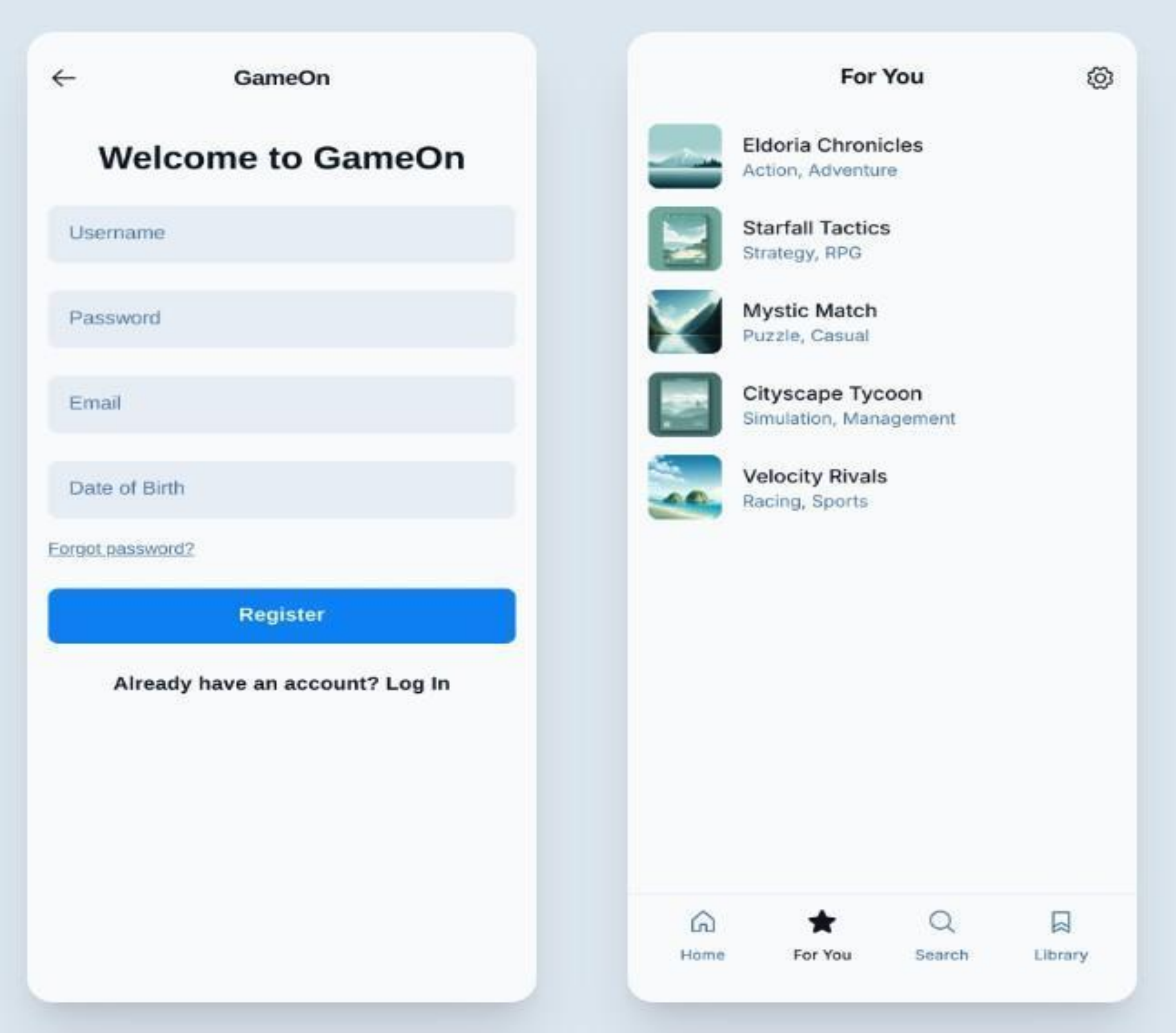


Figure 10: Output of Query 1 executed in phpMyAdmin



4. Interface Screenshot:

Figure 11: Query 1 result shown in the system interface

Query 2: Simple Selection

1. Plain English: Find the Id and Username of Users who have at least one record in the Play history table.

2. phpMyAdmin Screenshot:

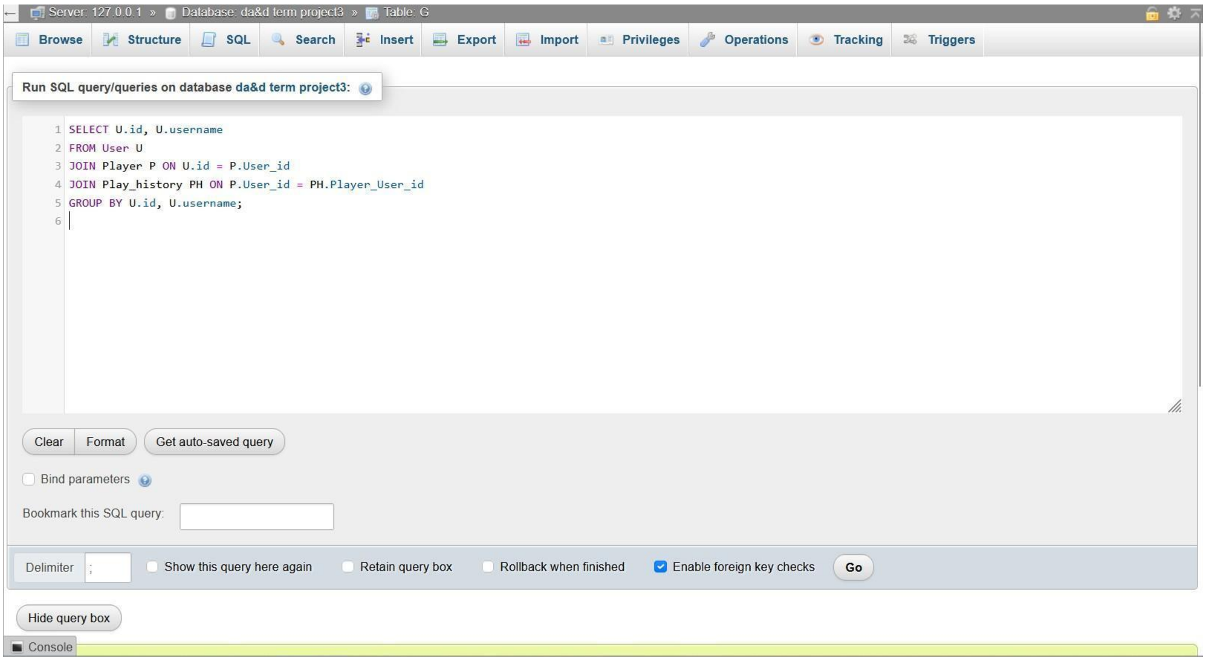


Figure 12: Input of Query 2 executed in phpMyAdmin

3. phpMyAdmin Screenshot:

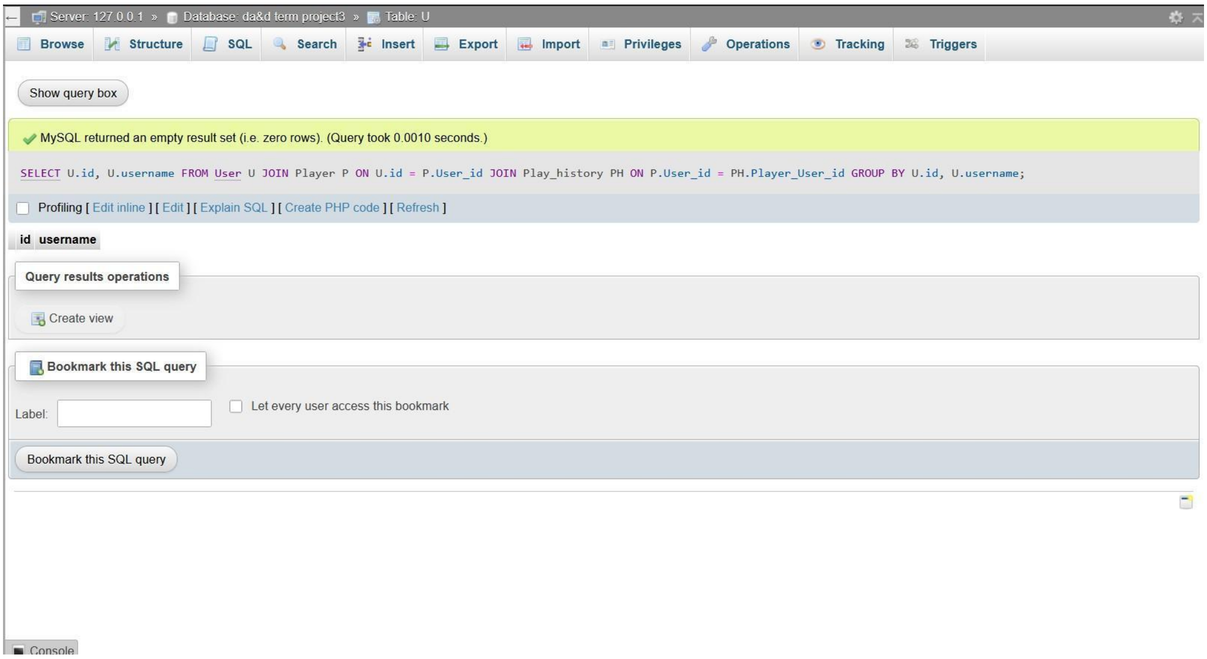


Figure 13: Output of Query 2 executed in phpMyAdmin

4. Interface Screenshot:

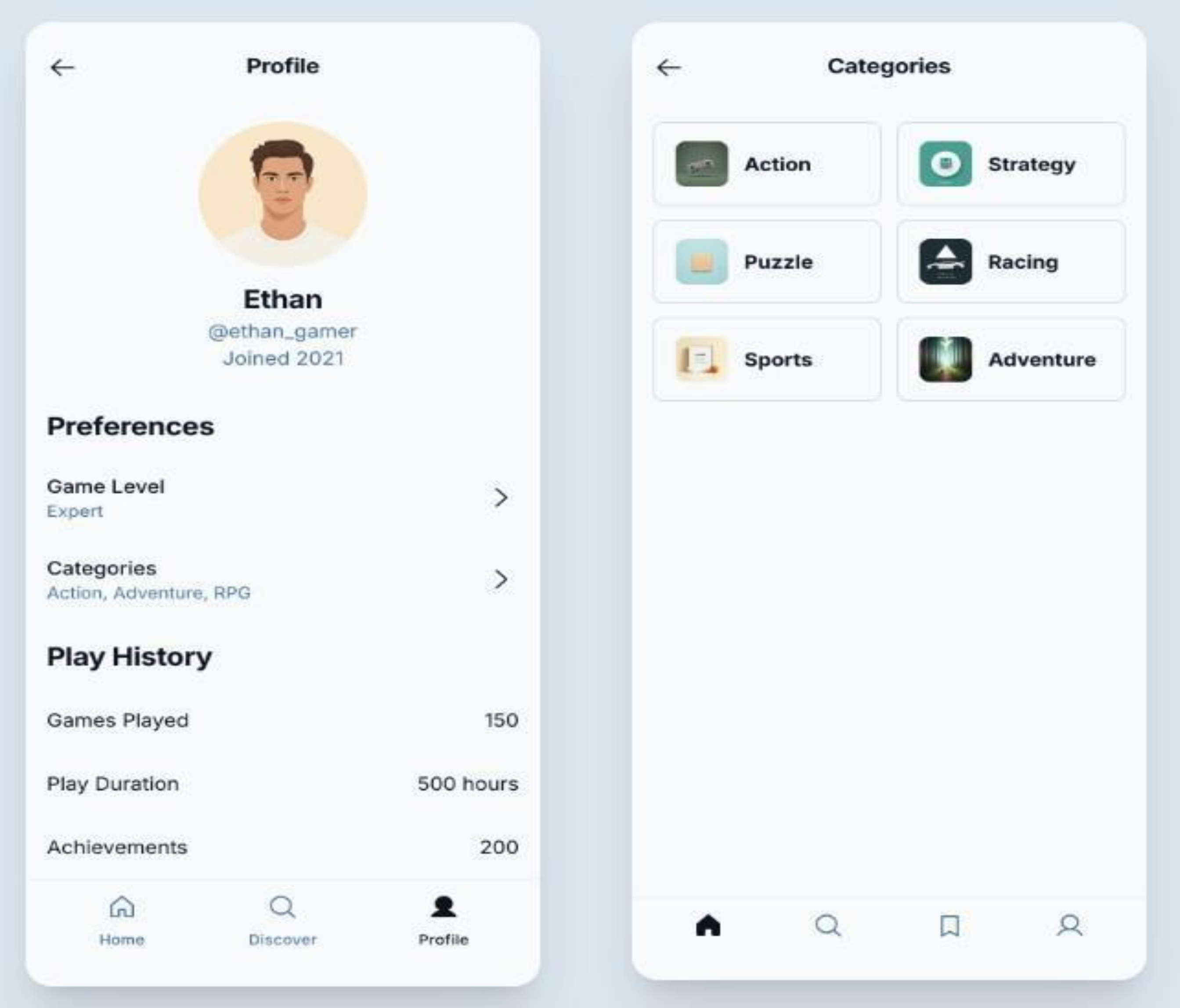


Figure 14: Query 2 result shown in the system interface

Query 3:

1. **Plain English:** Each time a user finishes playing, insert a new row into PlayHistory with session details.

2. **phpMyAdmin Screenshot:**

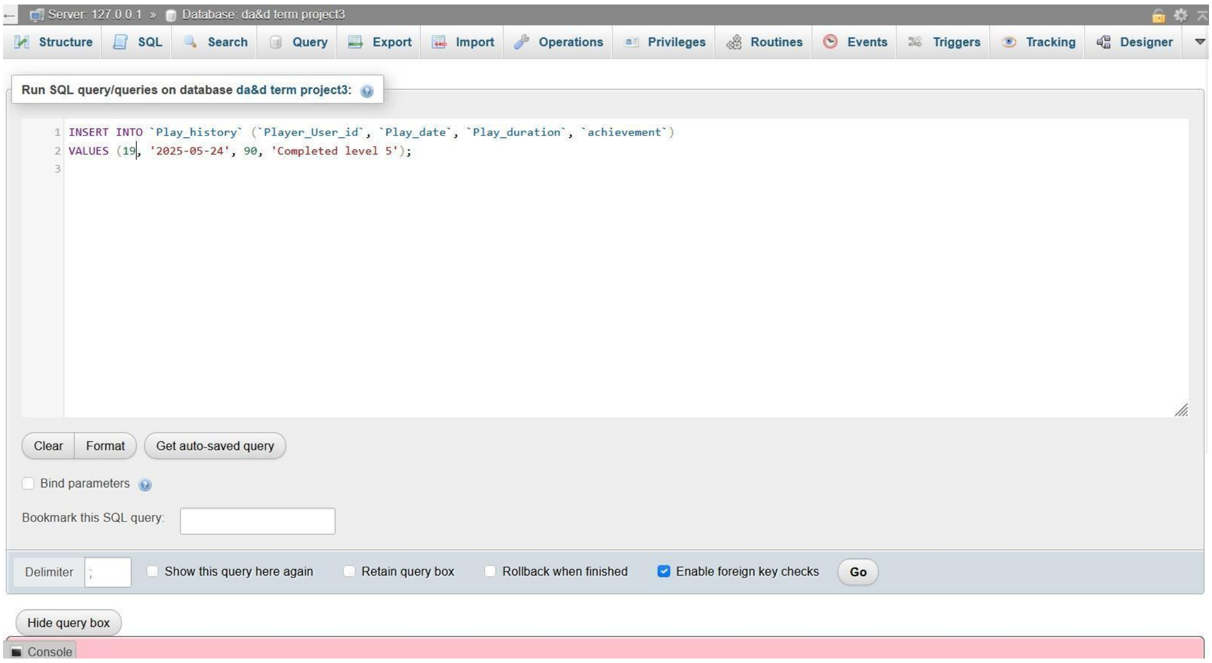


Figure 15: Input of Query 3 executed in phpMyAdmin

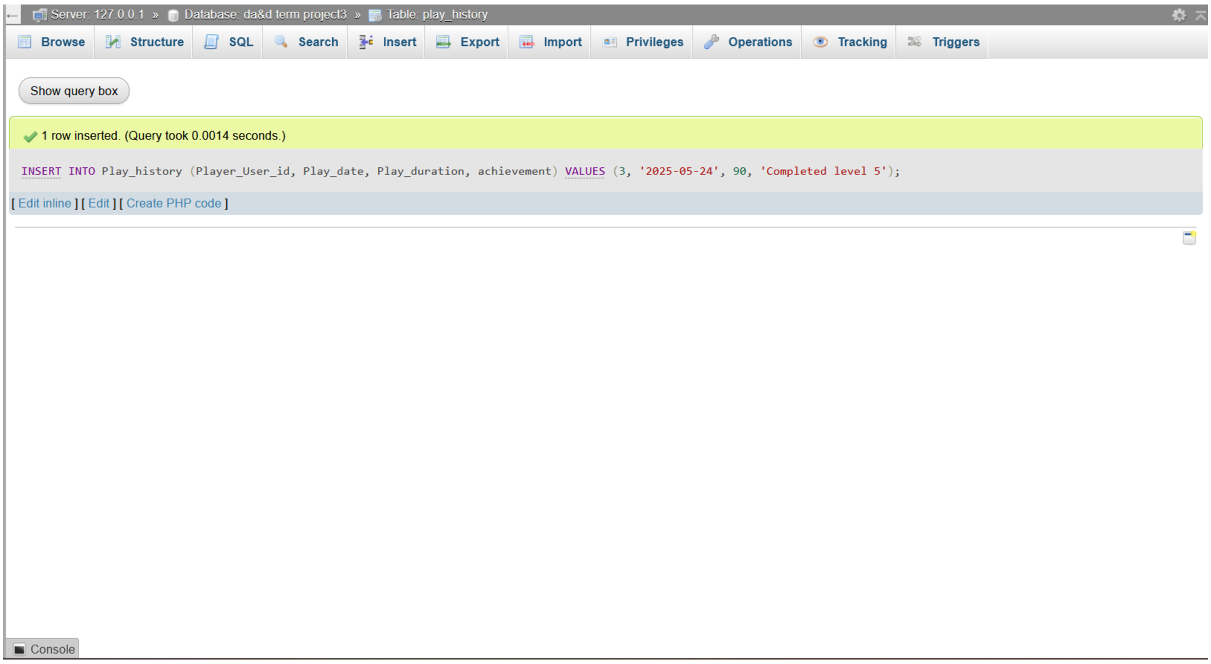


Figure 16: Output of Query 3 executed in phpMyAdmin

3. **Interface Screenshot:**

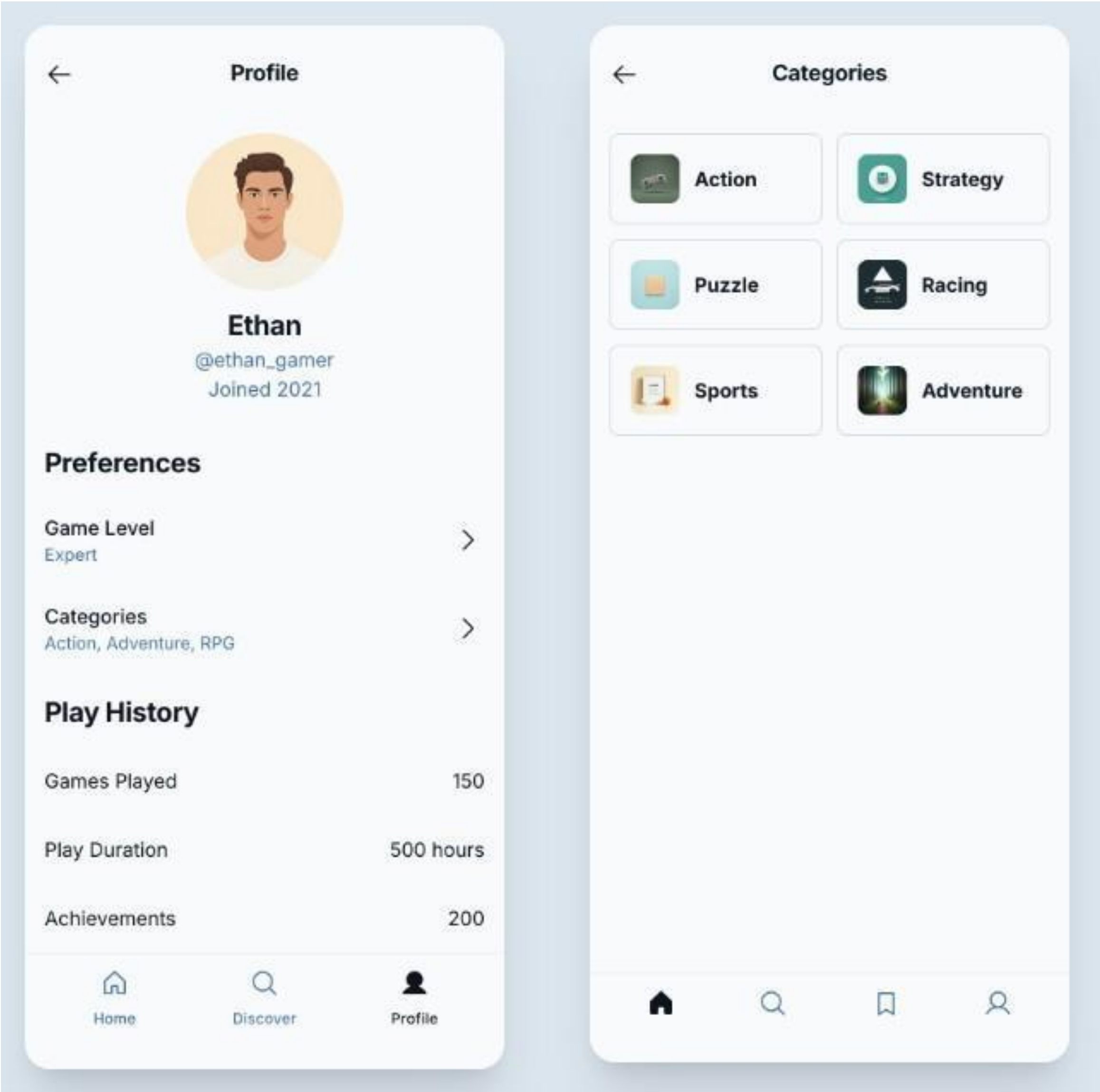


Figure 17: Query 3 result shown in the system interface

Query 4:

1. **Plain English:** List game titles with their category names for a specific category
2. **phpMyAdmin Screenshot:**

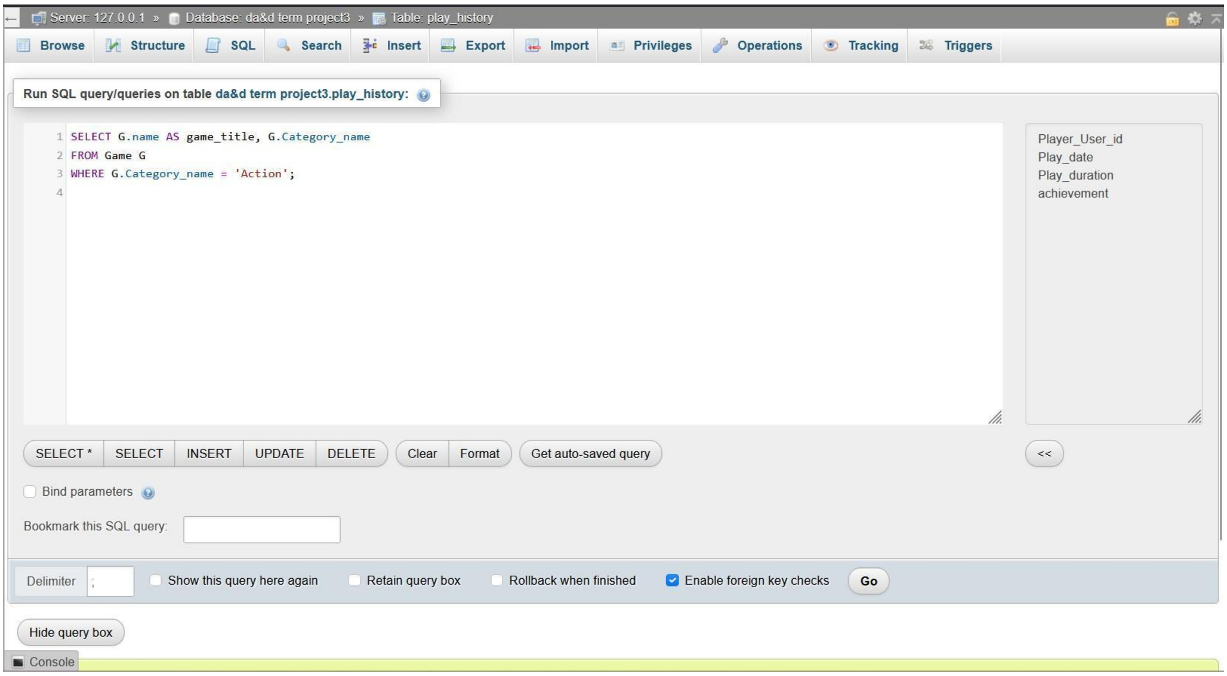


Figure 18: Input of Query 4 executed in phpMyAdmin

2. ***phpMyAdmin Screenshot:***

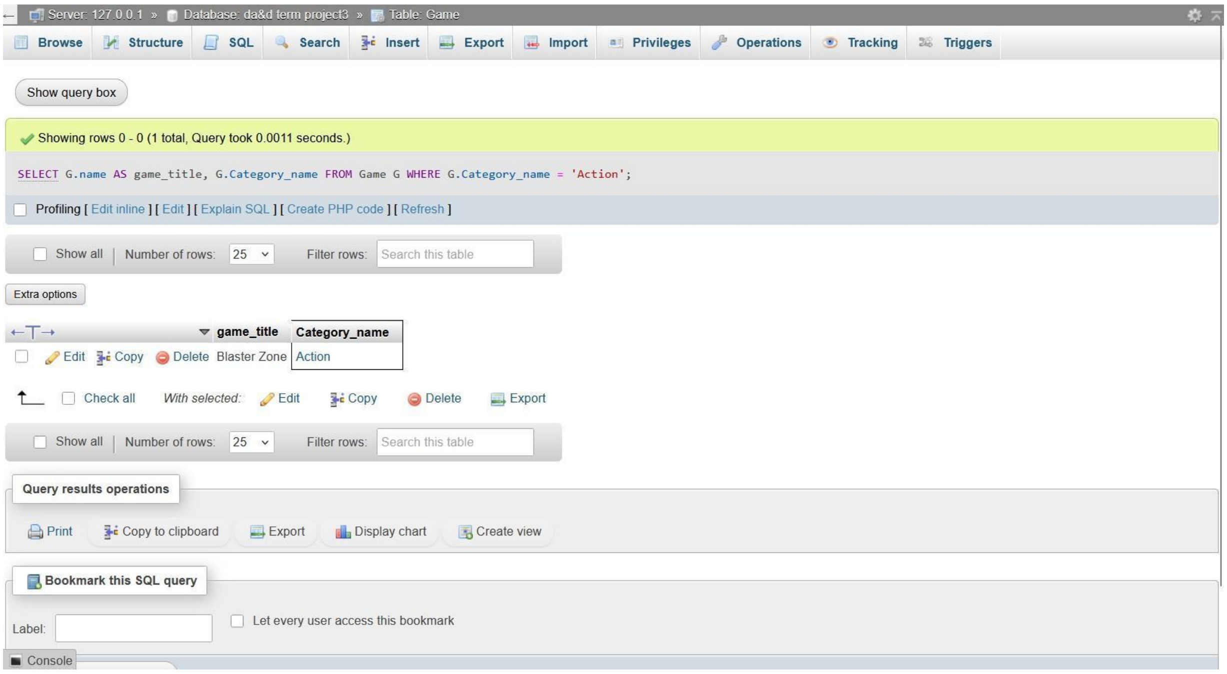


Figure 19: Output of Query 4 executed in phpMyAdmin

3. Interface Screenshot:

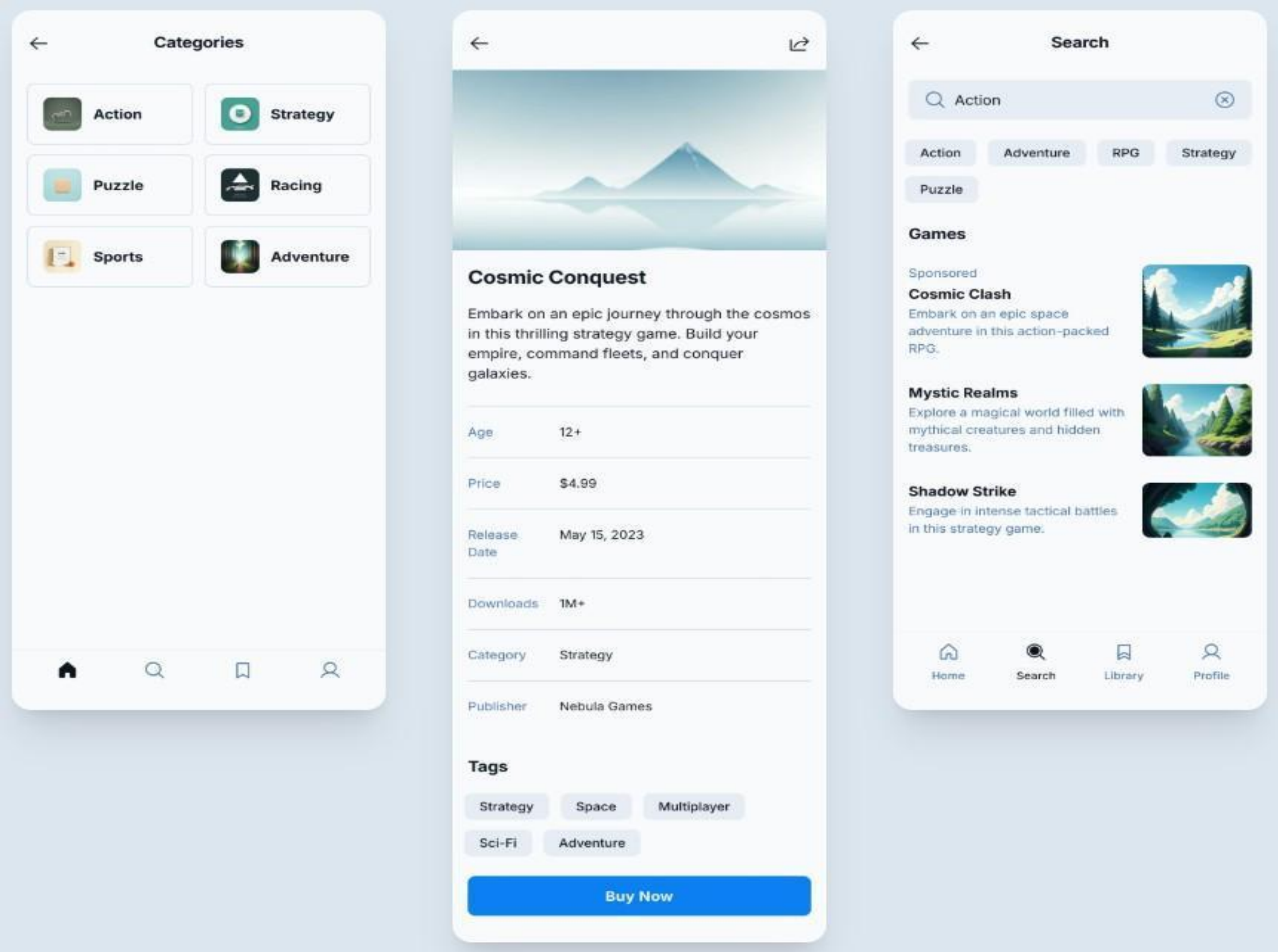


Figure 20: Query 4 result shown in the system interface

Query 5:

1. **Plain English:** Generate a list of Game recommendations for a user by correlating their Play history and Preferences with similar users' activities.

2. **phpMyAdmin Screenshot:**

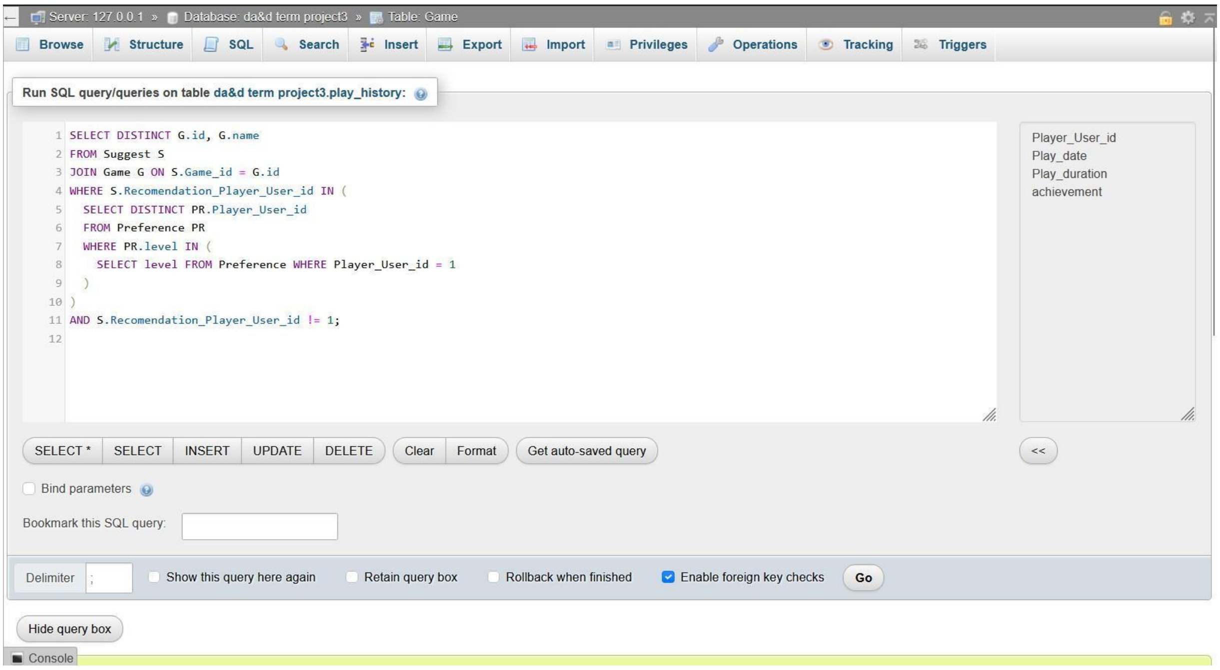


Figure 21: Input of Query 5 executed in phpMyAdmin

2. **phpMyAdmin Screenshot:**

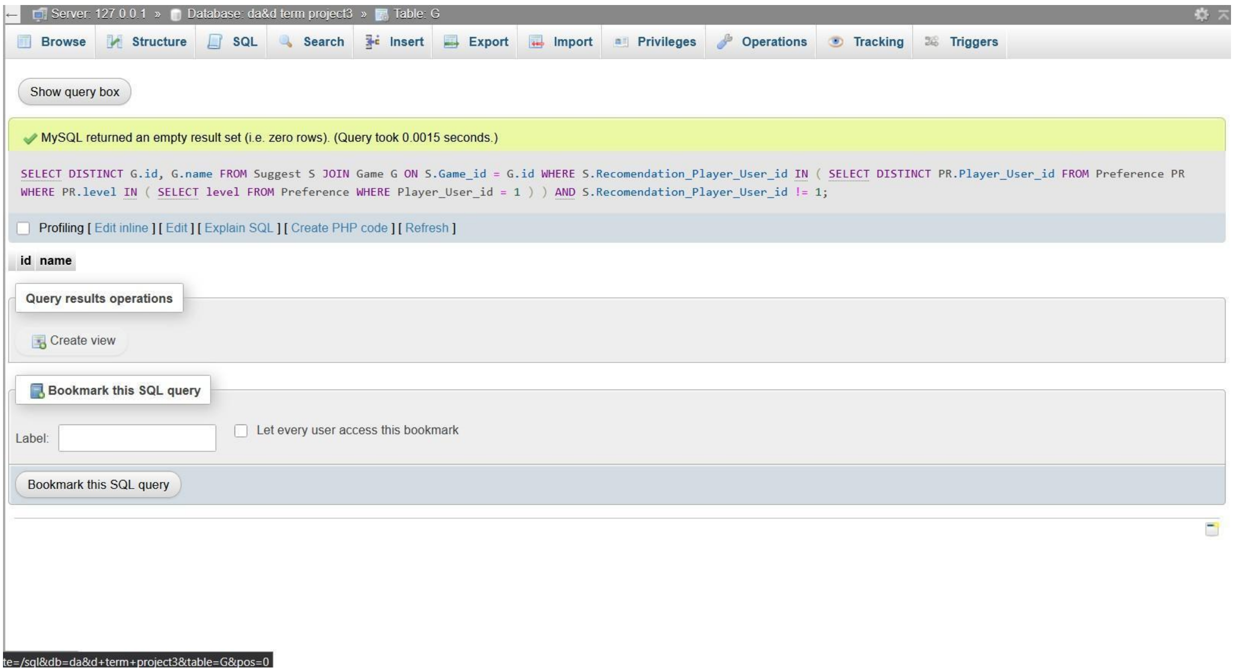


Figure 22: Output of Query 5 executed in phpMyAdmin

3. ***Interface Screenshot:***

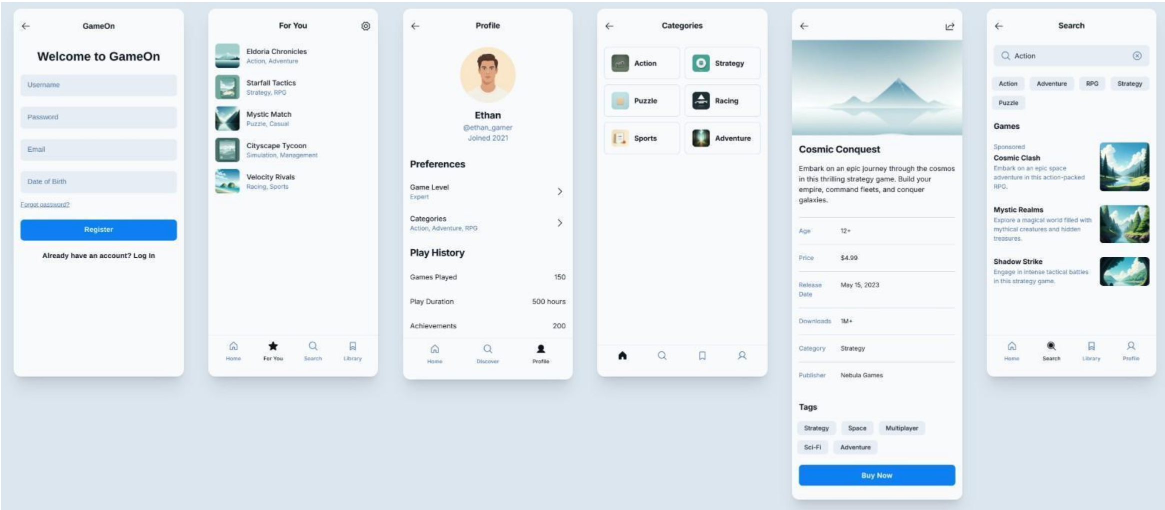


Figure 23: Query 5 result shown in the system interface

CONCLUSIONS

The project successfully illustrates the creation of a recommendation system for gaming pref- erences. By implementing some data sources: including user demographics, play history, and game atributes, our system enables game developers to better understand their audience and make informed decisions. The database design, along with conceptual and logical modeling, MySQL implementation, guarantees efficient data handling and retrieval.

Through the application of similarity metrics and analytics, the recommendation system that we developed provides user personalized suggestions that can enhance user experience and engagement. Furthermore the dashboard visualization can provide non technical stakeholders to find valuable insights into player behavior and preferences.

In summary this system connects the gap between raw game-play data and actionable marketing strategies. In the future further enhancements could include real-time analytics, deeper integration with game platforms, and the incorporation of machine learning models to improve recommendation accuracy further.

Open Issues and Future Work

While the current system successfully collects and analyzes gaming preference data through its ER model and SQL implementation, several opportunities for enhancement remain.First, advanced predictive analytics – Future iterations could incorporate machine learning algorithms to predict player preferences based on historical behavior patterns, enabling proactive rather than reactive marketing strategies.Second, real-time data processing – The current system processes data in batches. Implementing real-time streaming analytics would allow developers to respond immediately to emerging player trends and market shifts.Third, cross-platform integration – Expanding the system to aggregate data across multiple gaming platforms (PC, console, mobile) would provide more comprehensive player insights and improve targeting accuracy.Fourth, privacy-enhanced data collection – As data privacy regulations evolve, future work should focus on implementing federated learning and differential privacy techniques to protect user information while maintaining analytical capabilities.These enhancements would address current limitations and significantly improve the system's effectiveness in solving the fundamental challenge of audience targeting in the gaming industry.

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