DIGITAL PERFORMANCE TRACKING FOR AMATEUR FOOTBALL

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A PROJECT REPORT SUBMITTED TO THE FACULTY OF ENGINEERING, DESIGN AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A DEGREE OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE OF UGANDA CHRISTIAN UNIVERSITY

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UGANDA CHRISTIAN UNIVERSITY

A Centre of Excellence in the Heart of Africa

Declaration

We, the undersigned, declare to the best of our knowledge that the work in this proposal is original and has not been submitted before to any university or institution. It is the result of our collective effort as the FootyStats project group.

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Ethical Generative AI Usage Declaration

Students may use generative artificial intelligence (AI) ethically as a study buddy or assistant rather than a replacement for critical thinking. This includes citing AI use and fact checking all outputs to maintain academic integrity.

For purposes of this assignment, the following guidelines shall apply.

i. Generative AI may be used for brainstorming and generating ideas to improve your work. You may also use AI for literature search and summarizing journal papers for quick analysis and assessing relevance of publications. However, once the relevant publications have been identified, a student is expected to fully review the selected publications, identifying problems addressed, methods used, gaps identified and recommendations made.

ii. Where AI has been used as guided in (i) above, full disclosure of how it has been used should be made in Appendix C, including how AI was used, the AI tools (including model versions), and a compilation of major AI prompts used.

iii. NO GENERATIVE AI CONTENT IS ALLOWED IN THE FINAL SUBMISSION. The final submission SHOULD be your original work.

A. **Declaring the non use of AI for content generation**
We declare that no content generated by AI technologies has been used in this proposal.

B. **Acknowledging the use of AI as a study buddy**
Please refer to Appendix C for the complete declaration of AI usage for generating ideas, brainstorming, literature search, and summarizing only to improve your work.

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Approval

This proposal has been submitted for examination with the approval of the following advisors and supervisors.

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Abstract

Grassroots football draws millions of participants worldwide, yet most players still record performance through scattered channels such as paper notes, group chats, and one off social posts. Records are hard to compare, easy to lose, and rarely support any real analysis. Tools built for elite clubs depend on GPS feeds, video pipelines, and specialist staff that community leagues simply do not have.

This report presents *FootyStats*, a mobile platform that lets amateur players and tournament organisers log match events during play, store them in a shared database, and view leaderboards, player profiles, and simple performance trends. The work combines user centred design with a lightweight client server setup and automated aggregation so that useful summaries can be drawn from ordinary event data rather than costly tracking hardware.

Prototype testing showed that structured, low friction capture cuts down the fragmentation seen with informal methods, and that even basic match records can support meaningful summaries for grassroots users. The study offers both a practical path toward deployable amateur sports informatics and evidence that analytics can be delivered under the resource limits typical of community football.

Contents

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We sincerely thank our fellow **group members** for their reliability and collaboration: by consistently delivering their share of the work, they made it possible to complete this group project on schedule and to a standard we are proud of.

We also acknowledge the **Department of Computing & Technology** at Uganda Christian University for providing the learning environment, facilities, and administrative support that made this work possible.

Finally, we express our appreciation to amateur players, organisers, and others who engaged with our ideas or testing along the way, and to our friends for their encouragement during the final year.

Chapter 1

Introduction

1.1 Background

Amateur football is one of the largest participation sports globally. Community leagues, school tournaments, and weekend friendlies generate a steady flow of match activity, yet the way performance is recorded has changed little compared with professional environments. Elite clubs invest in analytics departments, GPS wearables, and video based tracking; grassroots players, by contrast, still depend on methods that were never designed for consistent statistical use.

The problem is not a lack of activity but a lack of structure. When a goal is scored or a card is issued, the information often ends up in a notebook, a WhatsApp thread, or a manually edited graphic for social media. Each channel uses a different format, nobody maintains a single source of truth, and historical records are difficult to retrieve. Organisers spend extra time compiling stats after matches, players cannot track their own progress reliably, and comparisons across tournaments remain subjective. Over time, valuable performance data is either lost or too inconsistent to support fair ranking, development feedback, or informed team selection.

This fragmentation matters because the wider sports analytics market is growing rapidly and data driven decision making is now normal at the professional level [4, 3]. Amateur football has been largely excluded from that trend. Existing digital products such as Hudl, StatsBomb, and Wyscout target academies, analysts, or professional scouts. They assume budgets, infrastructure, and data inputs that grassroots settings do not possess. The result is a persistent gap: millions of players produce match data every week, but few have access to tools that turn that data into structured, reusable information.

FootyStats was developed to address this gap. The platform is a mobile first system for recording core match events (goals, assists, cards, substitutions, and related actions) during or immediately after play. Entries are validated, stored centrally, and aggregated into player profiles, leaderboards, and shareable summaries. The design prioritises speed and simplicity so that a volunteer recorder or player can log events with minimal disruption to the match. By replacing scattered manual workflows with one integrated pipeline, FootyStats offers a realistic way to bring structured performance tracking to amateur football without requiring elite level resources.

The relevance of this solution extends beyond convenience. Structured statistics support player motivation, transparent competition, and better planning for organisers. For computer science, the project demonstrates how mobile development, database design, and lightweight analytics can be combined under tight budget and time constraints, conditions that mirror many real world deployments in emerging markets and community organisations.

1.2 Problem Statement

Amateur football players and organisers lack efficient and reliable tools for recording, managing, and analysing match statistics. Current methods (manual note taking, messaging platforms, and static social media posts) are fragmented, inconsistent, and difficult to maintain over time. Player performance data therefore remains unstructured and underused, limiting the ability to track progress, generate insights, or showcase achievements.

Existing digital sports analytics solutions are primarily designed for professional environments and rely on advanced data inputs unavailable in grassroots settings. Amateur players generate performance data but lack the means to convert it into structured, meaningful, and actionable information.

There is therefore a need for a lightweight, accessible, and integrated system that enables efficient data capture, automated processing, and clear presentation of results tailored to the constraints of amateur football.

1.3 Research Objectives

Main Objective:
To design and implement a mobile first digital platform that enables amateur football players and organisers to efficiently record, analyse, and visualise match performance data.

1. To design a mobile first application that allows quick in match recording of events (goals, assists, cards, substitutions, shots, etc.).

2. To implement a clear and simple data visualisation system that transforms recorded data into easy to understand summaries, enabling players to monitor progress and identify areas for improvement.

3. To ensure usability and accessibility of the system by creating an intuitive interface that requires minimal technical skills and works efficiently on commonly available devices.

1.4 Justification

This study is justified by the clear gap between advanced performance analytics in professional football and the lack of accessible tools for amateur players. Grassroots football generates substantial performance data, yet it remains largely unstructured because efficient tracking and analysis systems are missing.

By addressing this gap, the proposed system provides both practical and academic value. Practically, it empowers amateur players and organisers to record and manage performance data in a structured manner, improving visibility, engagement, and player development. Academically, the project shows how meaningful analytics can be derived from limited, low complexity datasets, a recurring challenge in applied data science.

The project also contributes to computer science by integrating mobile application development, data processing, and data visualisation within a single system. It aligns with demand for scalable, user centred digital solutions in underserved domains.

Ultimately, FootyStats offers a lightweight and extensible approach to digital performance tracking, providing a foundation for future enhancements such as richer analytics, recommendation features, and broader adoption within grassroots sports ecosystems.

Chapter 2

Literature Review

2.1 Literature Review Plan and Alignment with Objectives

This literature review follows a structured approach based on the PRISMA 2000 framework, as applied in the accompanying Systematic Literature Review (SLR; see `LIT REVIEW.tex`). Its purpose is to examine published work on digital performance tracking in football and related team sports, identify gaps, and connect those gaps directly to the research objectives defined in Chapter 1. The full Scopus corpus (**30** studies) plus two supplementary conference papers on match analytics appear in the REFERENCES section, including the major sources discussed below (e.g. Kranzinger et al., Malone et al., Buchheit & Laursen, Yang et al.).

The review is organised thematically around the three main objectives of this study:

- **(event recording):** Literature on mobile, event based data capture and real time logging in grassroots and youth football.
- **(visualisation):** Literature on dashboards, leaderboards, and interpretable presentation of sports performance data.
- **(usability and accessibility):** Literature on technology adoption, perceived ease of use, and design for non expert users in amateur settings.

Chronologically, the literature spans the shift from sensor heavy professional systems (2010 to 2015) through analytics frameworks (2016 to 2020) to mobile and AI integrated platforms (2020 onwards). This progression explains why professional tools dominate the literature while amateur needs remain under served.

1 Mobile and Event Based Performance Recording

Published work on sports tracking shows that accurate physical measurement often depends on GPS hardware and inertial sensors [5, 8]. Those systems suit elite environments but are costly and operationally demanding for community football. Rein and Memmert [4] describe how professional clubs adopted data driven tactical analysis, yet the underlying data streams are not available at grassroots level.

Kranzinger et al. [1] show that youth football can still be monitored with lighter tools, although many designs favour data volume over speed during live matches. Where a single volunteer records from the touchline, the literature points toward *event logging through mobile interfaces* rather than full wearable deployment. A persistent weakness is the lack of integrated workflows for fast in match entry; informal tools such as paper notes and chat apps remain common because formal systems are often too slow for informal match conditions.

2 Data Visualisation and Performance Summaries

As analytics matured, research emphasised presentation as much as collection. Mănescu [3] outlines big data frameworks for decision support in sport, while Moya et al. [2] examine advanced performance analytics in professional match settings. Both assume rich datasets, yet they agree that outputs must be understandable to decision makers.

For amateur users, clarity matters more than model complexity. Studies on sports visualisation report that rankings, trend lines, and match summaries sustain engagement better than raw tables. Leaderboards and player profiles recur as tools for motivation and comparison in youth sport research. Grassroots users need a focused subset (top scorers, assist tables, disciplinary records, and historical trends) rather than broadcast style dashboards. The literature therefore supports automated visual summaries built from basic events, without manual post match compilation.

3 Usability, Accessibility, and Technology Adoption

Usability research links perceived ease of use and perceived usefulness to continued adoption of digital systems. Frameworks such as the Technology Acceptance Model (TAM) and the System Usability Scale (SUS) appear across sports and health technology studies with similar findings: when a system disrupts workflow or demands technical skill, usage falls quickly.

Amateur football adds constraints of limited time during matches, variable connectivity, and mid range smartphones. Failures in grassroots technology are often traced to poor fit with context (too many fields, slow screens, or desktop dependence) rather than to algorithmic error alone. The literature supports mobile first, low friction interaction for tools intended for community football environments, a design direction reflected in the methodology chapter.

4 Research Gaps and Implications

Table 2.1 summarises the main gaps identified in the literature and the publications that provide evidence for each gap.

These gaps motivate the FootyStats design choices described in Chapter 3: mobile event capture, automated summaries, and user centred evaluation within resource limits typical of grassroots football.

Table 2.1: Research gaps and supporting references

Gap	Description	Evidence and references
1	Few integrated mobile tools support fast in match event logging for amateur organisers without professional infrastructure.	Youth and amateur studies note feasible tracking but weak workflow design for live entry; elite methods assume costly sensors [1, 5, 4].
2	Limited focus on automated roll up of basic events into leaderboards and profiles for grassroots users.	Decision support and analytics studies stress interpretable outputs; professional dashboards are not sized for sparse amateur data [3, 2].
3	Insufficient attention to long term adoption, workflow fit, and accessibility in community football.	Wearable and app research highlights cost, compliance, and usability barriers; informal tools persist when systems are slow or complex [5, 1, 30].
4	Over reliance on advanced data sources (GPS, video, elite tracking metrics) that amateur settings cannot supply.	Elite analytics literature depends on high resolution tracking; amateur data remain sparse and event limited [4, 2, 5].

Chapter 3

Methodology

3.1 Methodology

This study adopts a design science and user centred development approach to design, implement, and evaluate the FootyStats platform. The methodology focuses on building a functional system that addresses real world challenges in amateur football performance tracking while ensuring usability and technical feasibility.

The development process follows an iterative model consisting of four main stages: requirement analysis, system design, implementation, and evaluation. Each stage is informed by findings from the literature review and feedback from target users, including amateur players and tournament organisers. Figure 3.1 summarises the full research workflow from problem identification through evaluation.

1 Research Methodology Framework

The study followed a linear research process in which each phase informed the next. Work began by defining the grassroots stat recording problem, then reviewing published evidence, gathering requirements from players and organisers, analysing system needs, designing FootyStats, building a prototype, testing with users, and refining the solution from feedback. Figure 3.1 summarises this workflow.

2 Technology Acceptance Model (Conceptual Framework)

The Technology Acceptance Model (TAM) explains whether users adopt a new system. In this project, TAM is used as a conceptual lens: if users perceive FootyStats as easy to use and useful during matches, they are more likely to intend to use it and to continue recording stats. Perceived ease of use can also strengthen perceived usefulness when the app saves time compared with manual methods. Figure 3.2 shows these relationships.

3 Existing System versus Proposed System

Amateur teams today often follow an informal chain from match to social post: notes and messages are compiled manually, which produces inconsistent records. FootyStats replaces that chain with one application that records events, stores them centrally, and generates leaderboards and profiles automatically. Figures 3.3 and 3.4 contrast the two workflows.

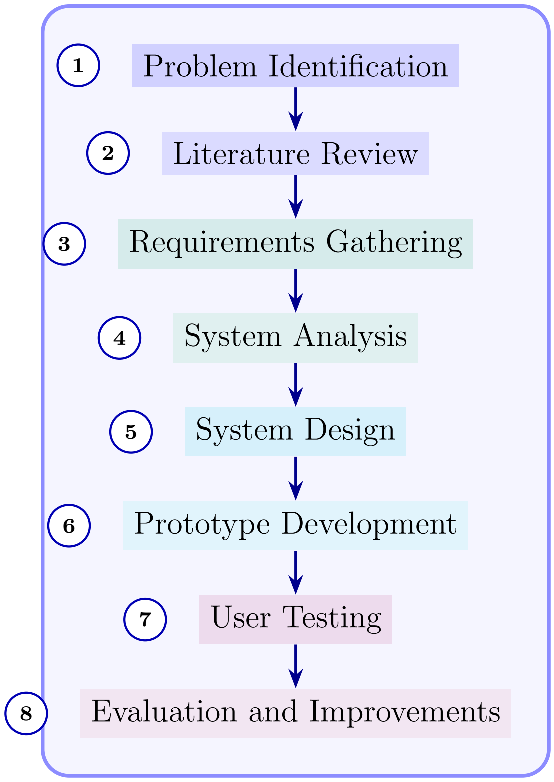


Figure 3.1: Research methodology framework for the FootyStats project.

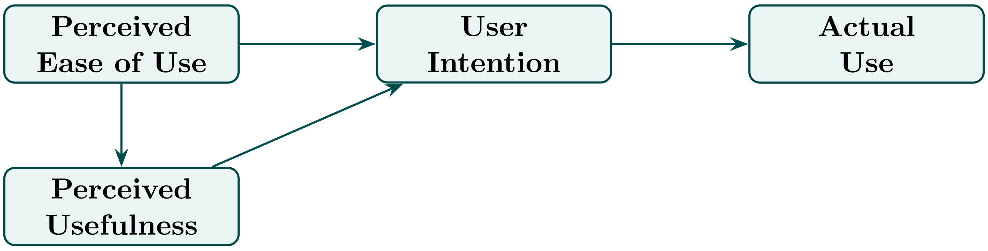


Figure 3.2: Technology Acceptance Model (TAM) applied to FootyStats adoption.

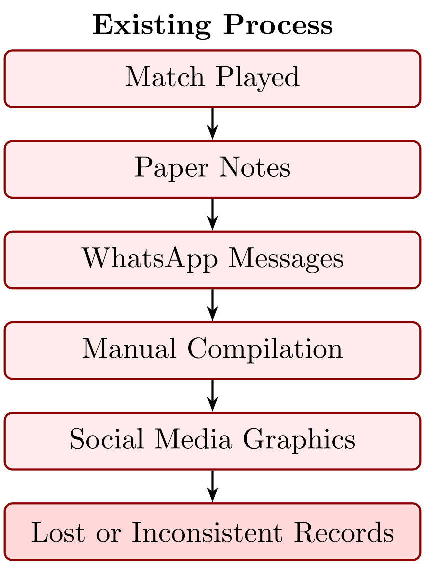


Figure 3.3: (a) Existing amateur stat recording process.

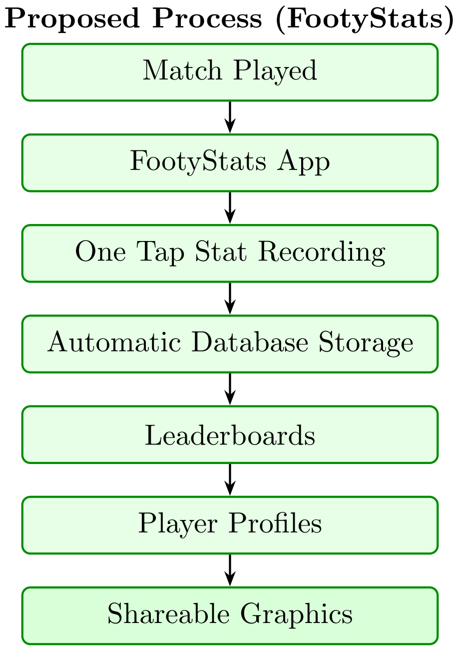


Figure 3.4: (b) Proposed FootyStats stat recording process.

4 System Architecture

FootyStats follows a client server layout. Players and organisers interact with the mobile app (client). The app sends events to application logic that validates and aggregates data. Structured records are stored in a database and then exposed as leaderboards, player profiles, and match history. Figure 3.5 shows how data moves between these layers.

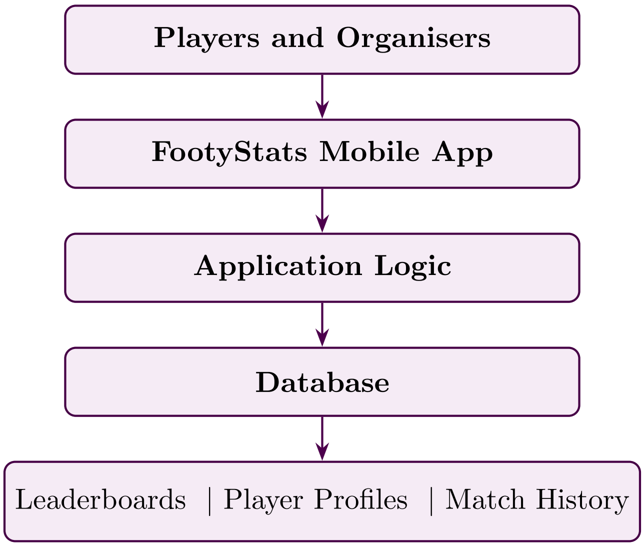


Figure 3.5: FootyStats system architecture.

5 Data Flow Diagram

A data flow diagram shows who supplies data, how the system processes it, and what outputs are produced. At context level (Figure 3.6), players and organisers submit match events to FootyStats; validated data are stored and then released as statistics and reports. Figure 3.7 expands this path from stat entry through validation and storage to leaderboards, player history, and social sharing.

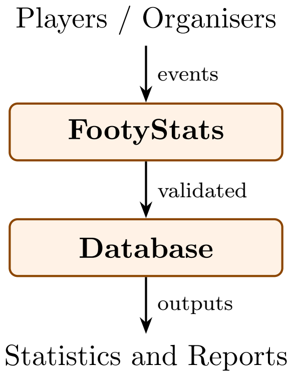


Figure 3.6: Data flow diagram, Level 0 (context diagram).

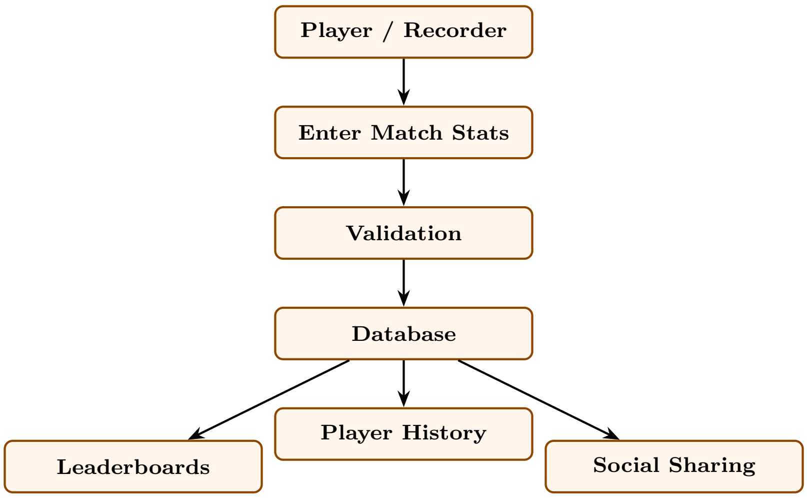


Figure 3.7: Data flow diagram, Level 1 (stat recording and outputs).

6 FootyStats Operational Pipeline

Each match event triggers a fixed sequence inside the system: the event is recorded in the app, validated, written to the database, used to refresh leaderboards and player profiles, converted into graphics, and optionally shared on social media. Figure 3.8 presents this operational pipeline.

7 Use Case Diagram

Use cases describe what each type of user can do in the system. Players record stats, view their performance, and share summaries. Organisers create matches, manage teams, view reports, and may also view stats. Figure 3.9 maps these roles to system functions using graphical action boxes linked to each actor.

8 Entity Relationship Model

The logical data model links players, teams, matches, and statistics for the **PHP/MySQL website**. A player belongs to a team; a team participates in matches; each match generates statistics tied to players. Figure 3.10 shows these entities and relationships. The **mobile app** persists a richer event set (including shots and substitutions) in **Supabase**; that schema is described in Section 3.3 and is intentionally omitted here so the website ERD stays aligned with the MySQL implementation.

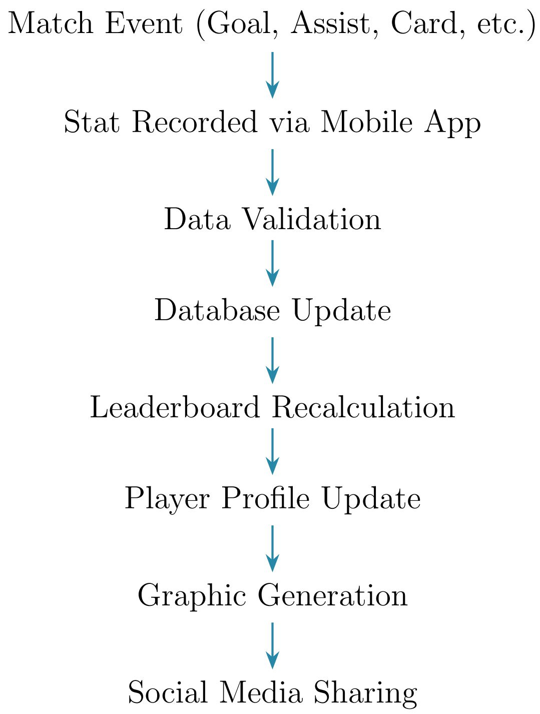


Figure 3.8: FootyStats operational pipeline from match event to shared output.

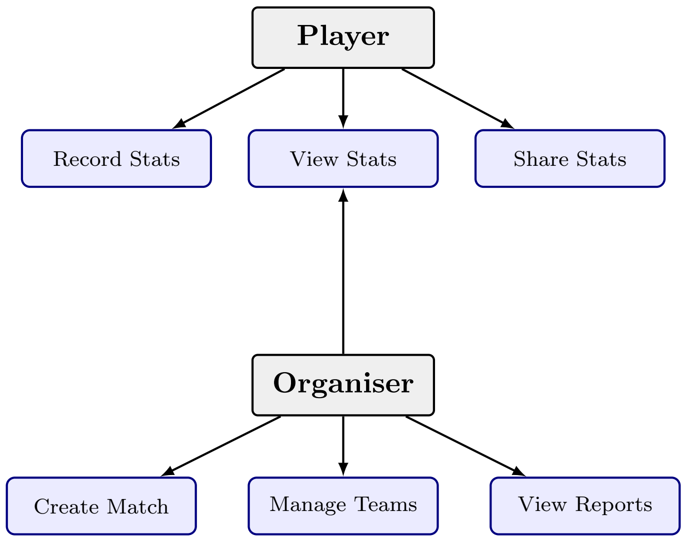


Figure 3.9: Use case diagram for FootyStats actors and core functions.

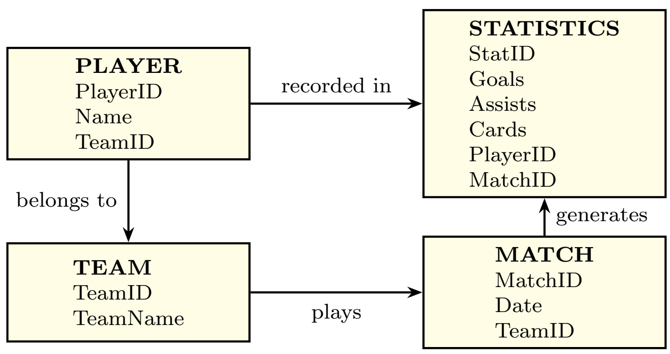


Figure 3.10: Entity relationship diagram for the PHP/MySQL website (goals, assists, cards per player per match).

3.2 System Design

The FootyStats system is designed as a mobile first, event driven architecture that captures, processes, and visualises football match data in real time. The system consists of three main components: data capture, data processing, and data presentation.

1 Architecture Overview

The system follows a client server architecture, illustrated in Figure 3.5:

- **Mobile client (Flutter):** Cross platform app for in match event recording and visualisation, connected to Supabase.
- **Web client (PHP):** Browser based pages and server logic for web access, backed by MySQL.
- **Application layer:** Validation of inputs, aggregation of statistics, and generation of summaries on the server and through Supabase services.
- **Data layer:** MySQL (website) and Supabase database (app) store match data, player statistics, and historical records.

This architecture ensures scalability, data consistency, and efficient processing of match events. Figure 3.10 shows the **MySQL** logical model for the **PHP website** (core match and player statistics for web access). The **Flutter mobile app** uses a separate **Supabase** (PostgreSQL) schema that additionally stores shots, substitutions, and other in match events required for live recording; those entities are not shown in Figure 3.10 because they belong to the app data layer, not the website ERD.

3.3 Data Collection Methods

Data collection in FootyStats is based on an event logging approach tailored to the constraints of amateur football environments.

1 Primary Data Collection

Primary data is collected through direct user input during matches. Users (players, referees, or organisers) record events such as:

- Goals scored
- Assists
- Shots (on or off target)
- Yellow and red cards
- Substitutions

Events are entered through the mobile app (Supabase backend). The website MySQL schema focuses on aggregated goals, assists, and cards for browser based leaderboards and profiles.

This approach ensures that data collection is simple, accessible, and does not require specialised equipment. The operational pipeline in Figure 3.8 shows how each recorded event moves through validation, storage, aggregation, and output generation.

2 Secondary Data Collection

Secondary data is obtained through user feedback mechanisms, including surveys and interviews conducted during the development phase. These inputs help identify user needs, usability challenges, and feature preferences.

3 Data Characteristics

The collected data is:

- **Low dimensional:** Limited to basic match events rather than complex tracking metrics.
- **Sparse:** Data is only recorded during matches.
- **User generated:** Dependent on manual input, introducing potential inconsistencies.

These characteristics directly shape how FootyStats processes information: the analytical module must work with short, irregular time series and simple event types rather than continuous tracking streams. Validation rules, aggregation logic, and visual summaries were therefore designed for sparse event logs so that partial or delayed entry still produces usable leaderboards and profiles without requiring professional grade sensor data.

3.4 Implementation Approach

The implementation of FootyStats focuses on developing a functional prototype using accessible and scalable technologies.

1 Development Strategy

An iterative development approach was used, allowing continuous refinement of the system based on user feedback. Initial prototypes were designed using Figma to visualise the user interface and interaction flow before implementation. Figures 3.3 and 3.4 highlight the workflow improvement FootyStats introduces over informal amateur methods.

2 Technology Stack

FootyStats uses a split technology stack for the website and the mobile application:

- **Website (web platform):** PHP with MySQL for server side logic, pages, and relational storage of match and player data accessed through the browser.
- **Mobile application:** Flutter for cross platform client development, with Supabase providing authentication, database, and backend API services for the app.

The website and app are designed to work with the same information model while using tools suited to each channel. Flutter handles in match recording and mobile visualisation; the PHP and MySQL website supports web based access and administration where required.

3 Analytical Component

A basic analytical module is integrated into the system to examine historical player data. Due to the limited nature of amateur football data, the module focuses on:

- Trend analysis of player performance over time

- Aggregated summaries such as goals per match and contribution totals
- Leaderboard and profile roll ups from stored events

The module is designed to operate effectively on small, noisy datasets, prioritising interpretability over complexity.

4 System Evaluation

The system was evaluated through prototype testing with amateur players and tournament organisers. Feedback was collected on how easy the app was to learn, how quickly stats could be entered during matches, and how clear the leaderboards and profile screens were. Evaluation also referred to TAM related ideas (perceived ease of use and perceived usefulness, Figure 3.2) so that test comments could be linked to adoption factors discussed in the literature. Use cases in Figure 3.9 guided test scenarios for both players and organisers. Results of this evaluation are reported in Chapter 4.

Chapter 4

Results and Discussion

This chapter reports what FootyStats achieved in practice and discusses what those outcomes mean: implications for amateur football, alignment with the literature in Chapter 2, and comparison with existing recording and analytics approaches. Results are presented first; discussion sections interpret findings rather than restate them.

4.1 System Implementation Results

The FootyStats platform was implemented as a functional prototype capable of capturing, processing, and visualising football match data. Users can record match events in real time; the system then produces structured outputs including player statistics, leaderboards, match summaries, and shareable graphics.

Compared with paper notes, messaging threads, and manual compilation, the prototype replaces several disconnected steps with the single pipeline described in Chapter 3. That consolidation is the primary functional result of the project.

4.2 Outputs and Analytical Results

Recorded match events generate the following outputs:

- **Player statistics:** Aggregated goals, assists, and disciplinary records per player.
- **Leaderboards:** Rankings such as top scorers and assist leaders.
- **Match summaries:** Structured records of key events and outcomes per fixture.
- **Performance trends:** Historical views of player contribution over time.
- **Shareable visual content:** Graphics suitable for social media distribution.

The analytical component produces trend indicators and aggregated performance summaries based on past matches. These outputs confirm that useful summaries can be derived from low dimensional event data without GPS or video inputs.

4.3 Evaluation Against Research Objectives

- **Mobile event recording:** Achieved. The prototype supports in match logging of core events through a mobile interface with minimal steps per action.

- **Data visualisation:** Achieved. Automated aggregation feeds leaderboards, profiles, and trend views without manual post match compilation.
- **Usability and accessibility:** Partially achieved. User testing indicated that the interface is learnable and usable on common smartphones, though long term adoption across diverse communities was not fully validated within the project timeframe.

4.4 Implications and Relation to Literature

The results should be read against the gaps and themes identified in Chapter 2. Gap 1 (integrated mobile workflows) is addressed in practice: FootyStats shows that structured capture on a phone can replace informal channels such as notebooks and chat threads [1, 5]. The implication for grassroots organisers is reduced post match compilation time and a single source of truth for tournament statistics.

Gap 2 (interpretable roll ups) is supported by user engagement with leaderboards and profiles rather than raw event lists [3, 2]. The implication is that amateur users value clarity and ranking over technical complexity, consistent with decision support literature that prioritises understandable outputs.

Gap 3 (adoption and workflow fit) appears in testing feedback aligned with Technology Acceptance Model themes: perceived ease of use rose when entry required few taps, and perceived usefulness rose when compilation time dropped [5, 30]. The implication is positive but tentative: the sample was small and geographically concentrated, so wider trials are needed before claiming sustained adoption.

Gap 4 (over reliance on elite data sources) frames the analytical scope. The module produced useful trends on sparse event logs but did not reach professional analytics depth [4, 2]. The implication is that lightweight aggregation and visualisation, not broadcast grade tracking suites, is the appropriate target for this context [3].

4.5 Comparison with Existing Solutions

Informal methods (paper, WhatsApp, manual graphics) remain the main competitor at grassroots level. FootyStats improves on them by centralising data and automating aggregation, but it does not remove the need for a diligent recorder during the match, the same human factor that limits informal methods.

Elite platforms (Hudl, StatsBomb, Wyscout) offer video, tracking, and advanced metrics aimed at academies and professionals [4, 2, 18]. They assume infrastructure, budget, and data inputs that community leagues lack. FootyStats deliberately trades depth for accessibility: no GPS vests, no video pipeline, and no specialist analyst role. Compared with those systems, FootyStats is weaker on tactical and physical detail but stronger on cost, speed of setup, and fit for volunteer recorders.

Wearable and sensor research shows that GPS and IMU devices can quantify load and movement when properly deployed [8, 5]. FootyStats does not compete on that axis; it could integrate such feeds later, but the current design targets clubs that will not purchase or maintain sensor kits.

FootyStats positioning. FootyStats demonstrates a reduced feature set (goals, assists, cards, shots, substitutions) with straightforward aggregation and dashboards. The comparison suggests a viable middle tier between informal notes and elite analytics suites, provided expectations are set correctly for amateur users.

4.6 Efficiency and Workflow Impact

Automation at the aggregation layer (not at the point of capture) delivers the largest immediate gain. Recorders still enter events manually, but once stored, statistics propagate to leaderboards and profiles without duplicate effort. Test users reported that end of tournament compilation, previously spread across chat logs and notebooks, could be shortened substantially.

The trade off is dependence on recorder diligence. Events that are never logged cannot be recovered. This mirrors the problem statement in Chapter 1 and remains a design boundary rather than a solved issue.

4.7 Usability and Adoption

Participants valued speed of entry and clarity of outputs over advanced metrics. Screens with many fields or ambiguous labels were avoided in later iterations. One tap patterns fit informal match conditions better than form heavy alternatives.

Adoption claims must remain cautious. Positive feedback indicates *potential* fit with grassroots workflows, not proven retention at scale. Repeated use across full tournament cycles would be required to validate long term behaviour.

4.8 Data Quality and Analytical Depth

Structured storage improves consistency relative to chat based recording, but quality still reflects human input. Missing assists, duplicate entries, or delayed logging were observed in testing. The analytical module handles sparse series reasonably for trends and rankings; it does not replicate professional tracking metrics built on GPS or video inputs.

For the target audience, that scope is appropriate. Amateur players primarily need comparable totals and visible progress. Pushing elite metrics on limited inputs would likely reduce trust rather than increase value.

4.9 Scalability and Technical Architecture

The client server architecture and modular pipeline support future extensions (additional stat types, organiser dashboards, or optional sensor feeds) without redesigning the core event path. Load testing at very high concurrency was not performed; scalability statements at this stage are architectural rather than empirically proven.

Flutter, Supabase, and PHP/MySQL accelerated delivery within the project timeline. Platform dependencies are acceptable for an academic prototype but should be reviewed if the system scales to larger user bases.

Visualized Results and Dashboard Outputs

This section presents selected outputs from the FootyStats dashboard and mobile interface. The figures illustrate how recorded match events are aggregated into leaderboards, player profiles, and team views that grassroots users can interpret without specialist analytics training. They extend the discussion above by showing how sparse amateur event data supports clear, actionable summaries rather than elite grade tracking.

4.9.1 Leaderboards and Player Profiles

Figure 4.1 shows the in app leaderboard used to compare players across categories such as goals and assists. Rankings update automatically from stored match events, removing the manual compilation step common in informal tournaments.

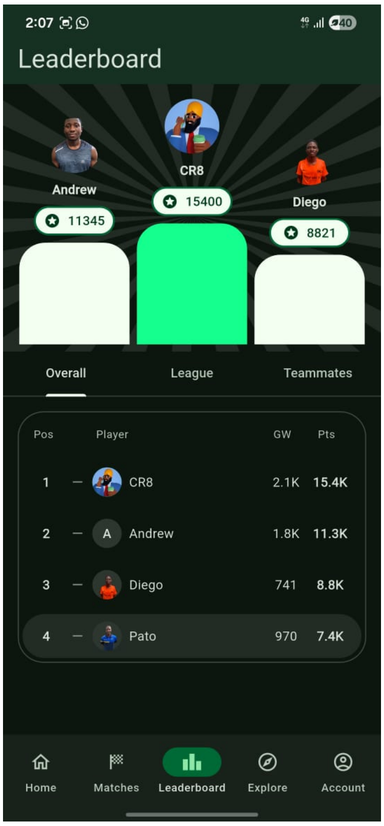


Figure 4.1: Leaderboard comparing player performance across recorded matches.

Figure 4.2 presents a player profile view with aggregated statistics and historical contribution. These screens translate raw event logs into summaries suitable for players, organisers, and social sharing.

4.9.2 Application Navigation and Match Recording

Figure 4.3 shows the home and explore screens that guide users to teams, fixtures, and recording flows. The layout prioritises low tap count during live matches.

In summary, these visualizations confirm that FootyStats can move beyond raw event logs to produce user facing dashboards for teams and individual players. They directly support the data visualisation objective (Objective 2) and the aggregation component described in Chapter 3. Additional interface screens appear in Appendix G.

4.10 Summary of Results and Discussion

FootyStats demonstrates that a lightweight, mobile first platform can convert basic match events into structured performance information for grassroots users. Results meet the core recording and visualisation objectives; usability findings are promising but not definitive. Discussion highlights manual capture as the main remaining bottleneck, sample size as the main validation constraint, and a deliberately narrow analytics scope as the right trade off for ama-

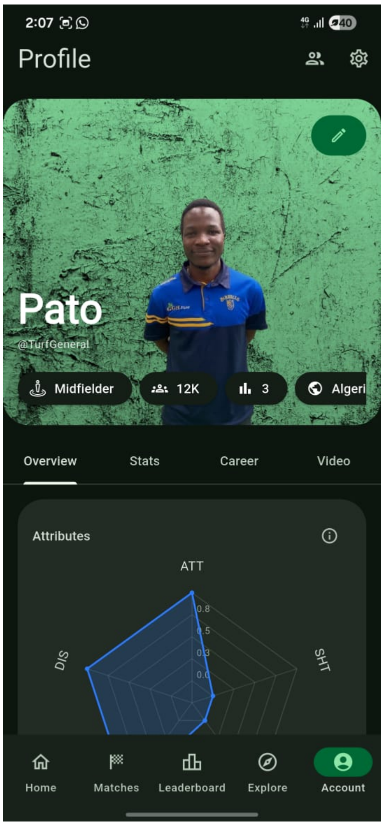
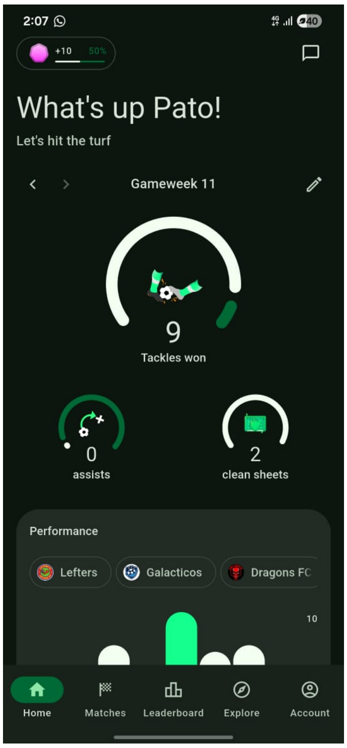
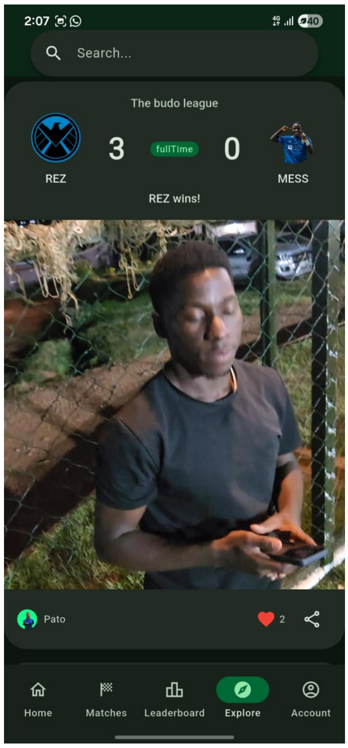


Figure 4.2: Player profile page with aggregated match statistics.



(a) Home screen.



(b) Explore screen.

Figure 4.3: FootyStats home and explore interfaces.

teur football. Chapter 5 concludes the study, states limitations, and outlines recommendations for future work.

Chapter 5

Conclusion, Limitations and Recommendations

5.1 Conclusion

This study addressed the lack of efficient and accessible performance tracking tools in amateur football by designing and implementing the FootyStats platform, a mobile first, event driven system for capturing, processing, and visualising match data.

The results show that simple, user generated match events can be transformed into structured performance insights. Automated aggregation into player statistics, leaderboards, and trend views reduces the fragmentation associated with paper notes and messaging platforms.

Overall, the project achieves its main objective of bridging the gap between grassroots participation and structured performance analytics, while acknowledging the constraints documented below.

5.2 Limitations

The following limitations were encountered during the FootyStats project lifecycle (proposal, design, development, validation, and pitch preparation). They are numbered for clarity.

1. **Limited real user data and small scale testing.**
   The project did not have access to a large dataset of amateur football statistics. Validation relied mainly on interviews, observations, and prototype testing within a limited number of tournaments and communities. Feedback was geographically constrained, so results may not represent all grassroots players and long term behaviour remains difficult to predict.

2. **Manual data entry dependency.**
   Statistics still depend on a person entering match events during or after play. Incorrect or missing inputs produce inaccurate aggregates. Real time accuracy depends on the recorder's attention and skill, which ties directly to the original problem of inconsistent stat recording methods.

3. **Scalability not yet demonstrated.**
   Expansion across many communities is proposed, but large scale adoption has not been tested. Infrastructure needs for high concurrent use (latency, database throughput, simultaneous stat updates) remain largely theoretical.

4. **Early market validation.**
   Interest was seen through tournaments and social media, but paying customers, retention rates, and revenue projections are not yet validated. FootyStats also competes indirectly with established platforms (Hudl, StatsBomb, Wyscout) that shape user expectations for analytics quality, even when those tools target different segments.

5.3 Recommendations for Future Work

In light of the findings and limitations above, the following directions are recommended:

- **Broader validation:** Run extended pilots across multiple regions and tournament formats to test adoption, retention, and data quality at scale.
- **Integration of advanced data sources:** Where budgets allow, incorporate wearables, GPS, or video assisted event detection to reduce manual entry and enrich metrics.
- **Richer statistical summaries:** Extend aggregation and visualisation as dataset size grows, while preserving interpretability for amateur users.
- **Automation of data capture:** Investigate semi automated logging (e.g., video based event tagging) to address the manual entry bottleneck.
- **Scalable deployment:** Secure funding for production hosting, monitor performance under load, and plan Supabase and MySQL scaling or migration if user numbers grow significantly.
- **Commercial validation:** Test pricing, subscriptions, and organiser led licensing models with real paying users.
- **Data privacy and security:** Implement robust protection measures as user bases grow, including clear consent and retention policies for player data.

FootyStats provides a workable foundation for digital performance tracking in amateur football. Future work should prioritise validation at scale, reduced dependence on manual capture, and sustainable funding while keeping the product aligned with the simplicity grassroots users actually need.

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Appendix A

Budget

Table A.1 summarises the estimated costs required to deploy and maintain the FootyStats platform. The budget includes backend services, app store publishing, media processing tools, and optional assistant features.

Table A.1: Estimated FootyStats deployment and operational budget in UGX.

Item	**Quantity**	**Unit cost (UGX)**	**Total (UGX)**
Supabase Pro Subscription (backend, auth, storage, analytics)	12 months	91,000	1,092,000
Google Play Developer account (one-time)	1	91,000	91,000
Apple Developer Program (iOS)	1 year	360,360	360,360
remove.bg API for player photos (OPTIONAL)	1 year	218,400	218,400
GPT API usage (AI assistant + summaries)	12 months	36,400–72,800	436,800–873,600
		Estimated total (range)	**2,198,760–2,834,360**

(Everything else is FREE to build with Flutter + Supabase + open-source packages.)

Appendix B

Research Project timelines

This appendix presents the full one-year management plan for FootyStats: how work is phased from initiation through deployment and final reporting, the dependencies between phases, and the week-by-week schedule (aligned with the project proposal). The schedule runs from **9th September 2025** to project completion by **28th February 2026**, with milestones organised into weekly iterations.

B.1 Phases, tasks, deliverables and dependencies

Table B.1 summarises how the year of work is grouped into phases. Each phase lists its span in weeks, main tasks, concrete deliverables, and what must be in place before that phase can start (dependencies). The detailed week-by-week breakdown follows in Table B.2.

B.2 Weekly workplan

Table B.2 presents the weekly workplan with measurable outputs for each week. The same schedule can be drawn as a one-page Gantt chart (phases on the vertical axis, weeks on the horizontal axis) for supervision or presentation.

Table B.2: Weekly workplan for the project from 9th September 2025 to 28th February 2026.

Week	**Date range**	**Key activities**	**Measurable outputs**
1	9–15 Sep 2025	Clarify project goals; agree on roles; set up version control, shared storage, and LaTeX template.	Project charter; role allocation; Git repository and LaTeX file created.
2	16–22 Sep 2025	Conduct needs assessment (interviews/forms); review 2–3 existing tools; organize funded tournament for data collection.	Requirements summary; competitor notes; pain points list.
3	23–29 Sep 2025	Define functional/non-functional requirements (user stories); decide on MVP features.	SRS draft; prioritised MVP feature list.

Week	Date range	Key activities	Measurable outputs
4	30 Sep–6 Oct 2025	Design system architecture (web client, admin dashboard, backend, database, mobile); choose technologies and hosting.	Architecture diagram; technology stack document.
5	7–13 Oct 2025	Design database schema (players, teams, matches, events, stats); check normalisation; plan indexes.	ERD diagram; SQL schema script.
6	14–20 Oct 2025	Set up database instance and backend structure; configure DB connection; expose health-check endpoint.	Backend skeleton connected; health-check tested.
7	21–27 Oct 2025	Implement backend endpoints for players, teams, matches (CRUD); add validation and error handling.	CRUD API working and tested.
8	28 Oct–3 Nov 2025	Extend backend for match event logging (goals, assists, cards, minutes) and automatic stat aggregation.	Event logging API; stat aggregation confirmed.
9	4–10 Nov 2025	Build web client v0.1: login, create teams/players, create matches linked to competitions.	Web app v0.1 with sign-in and basic forms.
10	11–17 Nov 2025	Add match event logging interface (forms/buttons for goals, assists, cards); show per-match summary.	End-to-end flow working; summary view visible.
11	18–24 Nov 2025	Develop admin dashboard: list teams, players, matches with filters (date, competition).	Admin dashboard v1 with lists and filters.
12	25 Nov–1 Dec 2025	Implement leaderboards (top scorers, assists, clean sheets) using aggregated queries; add pagination/search.	Functional leaderboards for at least two categories.
13	2–8 Dec 2025	Design mobile app prototype (Figma/wireframes): personal stats, team stats, leaderboards.	Clickable mobile prototype with main flows.
14	9–15 Dec 2025	Implement mobile client/responsive views: read-only endpoints for player and team stats.	Mobile v0.1: "My Stats" and "Team Stats" pages.
15	16–22 Dec 2025	Refine UI/UX: consistent colours, typography, navigation; add loading indicators and error messages.	Polished UI; usability checklist and screenshots.
16	23–29 Dec 2025	Prepare pilot: identify team/tournament; create test accounts; finalise consent forms and questionnaire.	Pilot plan; test accounts; feedback form ready.
17	30 Dec 2025–5 Jan 2026	Run first pilot (live/simulated match); collect feedback from organisers and players.	Match events dataset; completed feedback forms; observation notes.
18	6–12 Jan 2026	Clean match data; define performance indicators (goals per game, average minutes, contribution index).	Structured dataset; performance indicator calculations.

Week	Date range	Key activities	Measurable outputs
19	13–19 Jan 2026	Add analytics dashboards: charts for player/team performance over time (goals per match, form trends).	Analytics dashboard v1 with at least two charts.
20	20–26 Jan 2026	Develop performance insight module: label players as "on form"/"needs improvement" based on recent stats.	Performance insight service v1; endpoint returning player labels.
21	27 Jan–2 Feb 2026	Surface insights in UI: badges/highlights on profiles and leaderboards; gather tester feedback.	Form-based badges in UI; feedback summary on usefulness/accuracy.
22	3–9 Feb 2026	Prototype stats assistant (chat interface) answering pre-defined queries using database templates.	Chat interface v0.1 handling at least 5 query types.
23	10–16 Feb 2026	Full integration testing (web, admin, backend, database, mobile, analytics, assistant); fix bugs.	Integration test report; critical bugs fixed; system stable.
24	17–23 Feb 2026	Final polish: clean code/database, update documentation, capture screenshots/demo, prepare slides/poster.	Final prototype; updated documentation; slide deck/poster and progress report.
25	24–28 Feb 2026	Project closure: final report submission and presentation preparation.	Completed report; presentation materials ready.

Table B.1: High-level project phases, deliverables and dependencies.

#	Weeks	Focus	Key deliverables	Dependencies
1	1–3	Initiation & requirements	Project charter; roles; repository; needs assessment; requirements summary; SRS draft; MVP feature list	None (project kick-off)
2	4–8	Design & backend core	Architecture diagram; tech stack; ERD and SQL; backend skeleton; CRUD API; event logging and stat aggregation	Phase 1 outputs (requirements, MVP scope)
3	9–12	Web client, admin & leaderboards	Web app v0.1; match logging UI; admin dashboard; leaderboards	Stable backend APIs (Phase 2)
4	13–16	Mobile, UX & pilot prep	Mobile prototype; read-only stats; UI polish; pilot plan; test accounts; consent and questionnaires	Core platform usable on web (Phase 3)
5	17–18	Pilot & structured data	Pilot execution; feedback forms; cleaned match dataset; performance indicators	Pilot assets and test accounts (Phase 4)
6	19–21	Analytics & insights	Analytics dashboards; performance insight labels; badges/highlights in UI	KPI definitions and dataset (Phase 5)
7	22–25	Advanced features & closure	Stats assistant chat; full integration testing; documentation; demo and poster/slides	Integrated web, mobile, backend and analytics (Phases 2–6)

Appendix C

Declaration of AI use

Declaration statement

i. **Artificial intelligence.** We, *Kisuze Gareth Neville*, *Katende Derrick Elvan*, and *Ogwang Andrew*, used AI tools only as support during development, debugging, and academic structuring. All AI outputs were reviewed, edited, and validated before inclusion.

ii. **GitHub Copilot.** Used for code suggestions in Flutter and backend logic; generated snippets were reworked and tested for correctness and maintainability.

iii. **Stack Overflow (AI assisted and community resources).** Used for troubleshooting (e.g., layout overflow and Supabase auth/RLS); adopted solutions were adapted to FootyStats and verified through testing.

Signature: ____________________ Date: 2 June 2026

Kisuze Gareth Neville

Signature: ____________________ Date: 2 June 2026

Ogwang Andrew

Signature: ____________________ Date: 2 June 2026

Katende Derrick Elvan

Appendix D

Scopus Search Strings used during the literature review

The systematic literature review that underpins this project followed PRISMA 2000 and used **Scopus exclusively** as the bibliographic database. Searches covered publication years from **January 2010 to March 2025**, restricted to **English**-language records. Results were exported for screening and deduplication; in total, **105** records were identified via Scopus, and **30** journal studies were included in the synthesis after duplicate removal and title/abstract/full-text screening (see the SLR document for eligibility criteria).

D.1 Thematic search clusters

Four thematic clusters were defined to reflect the FootyStats concept and to structure query design:

- **C1:** Amateur/Grassroots Football Analytics
- **C2:** Sports App Usability and Adoption (e.g., SUS/TAM)
- **C3:** Wearables and Real-Time Tracking in Football and Team Sports
- **C4:** Dashboards and Performance Visualisation for Sports Insights

Cluster-specific searches were built by combining context terms (football/amateur/grassroots, etc.) with technology and method terms drawn from each cluster. The blocks below compile the **Scopus Advanced Search** strings and **keyword groups** used to retrieve publications for screening.

D.2 Index terms and recurring keywords

The following index-style keywords align with the SLR and were used alongside the structured queries for discovery and screening consistency:

> Sports Technology; Amateur Football; PRISMA 2000; Scopus; Usability; Wearables; AI Dashboards; Sports Analytics.

Additional recurring **TITLE-ABS-KEY** term groups used when refining cluster queries included:

- **Population / context:** `amateur`, `grassroots`, `"youth soccer"`, `"university football"`, `football`, `soccer`, `"team sport*"`
- **Functions / outcomes:** `"match stats"`, `"performance tracking"`, `analytics`, `"event logging"`, `platform`, `"mobile app"`, `"AI dashboard"`
- **Usability / adoption (C2):** `SUS`, `TAM`, `usability`, `"technology acceptance"`
- **Wearables / sensing (C3):** `"GPS"`, `"IMU"`, `"wearable sensor"`, `inertial`
- **Dashboards / visualisation (C4):** `dashboard`, `visualization`, `analytics`, `"performance insight*"`

D.3 Example advanced query (C1 and C2 combined)

The SLR documented one representative advanced query combining amateur/grassroots football analytics with mobile/platform and analytics-oriented terms relevant to C1 and C2. It was expressed in Scopus as follows (reproduced from the systematic review):

```
TITLE-ABS-KEY(
(amateur OR grassroots OR "youth soccer" OR "university football")
AND ("match stats" OR "performance tracking" OR analytics OR
 "event logging")
AND ("mobile app" OR platform OR "AI dashboard")
)
AND PUBYEAR > 2010
AND (LIMIT-TO(LANGUAGE, "English"))
```

D.4 Cluster-specific query extensions

Further queries were obtained by **substituting technology and method terms** while keeping the same database, year, and language limits. Representative constructions are given below.

D.1 Wearables and real-time tracking (C3)

The wearables-oriented term group documented in the SLR was:

```
("GPS" OR "IMU" OR "wearable sensor" OR "inertial")
```

A full Scopus-style query used for cluster C3 combined this group with football/team-sport context and performance/load terminology:

```
TITLE-ABS-KEY(
(football OR soccer OR amateur OR grassroots OR "team sport*")
AND ("GPS" OR "IMU" OR "wearable sensor" OR "inertial")
AND ("performance tracking" OR "external load" OR workload
 OR analytics OR "real-time")
)
AND PUBYEAR > 2010
AND (LIMIT-TO(LANGUAGE, "English"))
```

D.2 Dashboards and performance visualisation (C4)

The visualisation-oriented term group documented in the SLR was:

```
(dashboard OR visualization OR analytics OR "performance insight*")
```

A full Scopus-style query used for cluster C4 combined this group with football/amateur context:

```
TITLE-ABS-KEY(
(football OR soccer OR amateur OR grassroots)
AND (dashboard OR visualization OR analytics OR "performance insight*")
AND ("match stats" OR "performance tracking" OR "event logging")
)
AND PUBYEAR > 2010
AND (LIMIT-TO(LANGUAGE, "English"))
```

D.5 Reproducibility note

The final set of strings and filters was documented in the SLR so that the search process can be **replicated or extended** (for example, by adding Web of Science or other databases in future work). Minor variations in parentheses, wildcards (*), or field tags may change hit counts slightly between Scopus interface versions; the blocks above preserve the logic described in the systematic review.

Appendix E

Research alignment with specialization, SDG, NDPIV & Vision 2040

E.1 Alignment with Programme Specialization

Selected track: Machine Learning & Data Analytics

This research aligns with the Machine Learning & Data Analytics specialization through the collection, processing, and visualisation of football performance data. The proposed system captures match statistics and transforms them into structured summaries, leaderboards, and trend views that support decision making for amateur players and organisers.

The project demonstrates core data analytics practices such as:

- Data validation and aggregation from user generated event logs
- Database design and consistent storage across mobile and web clients
- Clear visual presentation of performance information for non expert users

By bridging raw data collection with accessible presentation, the system shows how data driven tools can be applied in real world, resource constrained environments like grassroots football.

E.2 Alignment with Sustainable Development Goals (SDGs)

This research aligns with United Nations Sustainable Development Goals, particularly:

SDG 3: Good Health and Well-being

- Encourages active participation in sports by making performance measurable and motivating players to improve.
- Promotes physical fitness and healthy lifestyles among youth and amateur athletes.

SDG 8: Decent Work and Economic Growth

- Creates opportunities for players to showcase talent through recorded statistics and performance profiles.
- Supports the sports ecosystem by enabling visibility for grassroots talent, potentially leading to professional opportunities.

SDG 9: Industry, Innovation, and Infrastructure

- Introduces an innovative digital solution in a space dominated by manual processes.
- Enhances technological adoption in sports at the grassroots level.

E.3 Alignment with the National Development Plan IV (NDP IV)

This research aligns with Uganda's National Development Plan IV, which emphasizes digital transformation and private sector-led growth.

Key areas of alignment

Digital transformation agenda. The system promotes digitization by replacing manual stat tracking (paper, WhatsApp, social media) with a centralized digital platform.

Human capital development. By enabling performance tracking and visibility, the platform contributes to talent identification and development in sports.

Private sector development & innovation. The project supports entrepreneurship and innovation in Uganda's growing tech ecosystem by introducing a scalable sports-tech solution.

E.4 Alignment with Uganda Vision 2040

This research aligns with Uganda Vision 2040, which aims to transform Uganda into a modern, industrialized, and knowledge-based economy.

Key contributions

Knowledge-based economy. The system promotes the use of data and analytics in decision-making within sports, shifting from informal practices to structured, data-driven approaches.

ICT and innovation development. The project contributes to ICT sector growth by developing a digital platform tailored to local needs.

Youth empowerment and talent development. With a large youth population, the platform supports talent exposure and development through measurable performance records.

Appendix F

Algorithms, Code of interest

This appendix summarises the main **algorithms** and **representative code** used in the FootyStats project. The primary codebase is the **Flutter** mobile app in `FootyStats app/footystats/`, with supporting web logic in PHP and MySQL.

F.1 FootyStats app: round robin fixture generation

F.1 Circle method

League fixtures are generated client side in `lib/domain/services/fixture_generator.dart`. For an even or odd number of teams, the implementation uses the **circle (round robin) method**: pair endpoints of a rotating list each round, skip a `_bye` slot when the count is odd, and **rotate** positions $2, \ldots, n$ while keeping one index fixed. Double legs and home/away swaps are supported; an alternative mode packs **full rounds per gameweek** with greedy ordering to reduce back to back matches for the same team.

Listing F.1: Core pairing and rotation (`fixture_generator.dart`).

```
for (var r = 0; r < numRounds; r++) {
  for (var i = 0; i < matchesPerRound; i++) {
    final a = current[i];
    final b = current[teams.length - 1 - i];
    if (a != _bye && b != _bye) {
      roundMatches.add((a, b));
    }
  }
  if (r < numRounds - 1) {
    current = _rotate(current);
  }
}
/// Rotate indices 1..n-1 clockwise; index 0 stays fixed (circle method).
static List<String> _rotate(List<String> list) {
  if (list.length <= 1) return list;
  final rest = list.sublist(1);
  final rotated = [rest.last, ...rest.sublist(0, rest.length - 1)];
  return [list[0], ...rotated];
}
```

Appendix G

Other useful figures

The following figures show additional FootyStats interface screens. All of these screenshots are available at:

https://www.figma.com/design/CBG6XFYCPv2PdqDuesmKEb/Footy-original-final?node-id=0-1&p=f

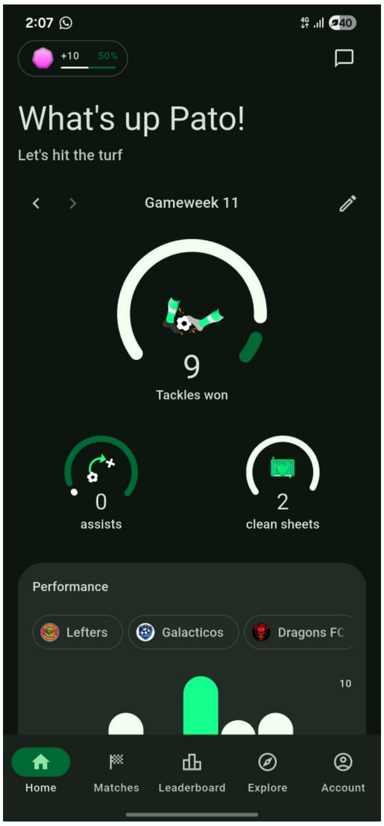

Figure G.1: Home page after opening application.

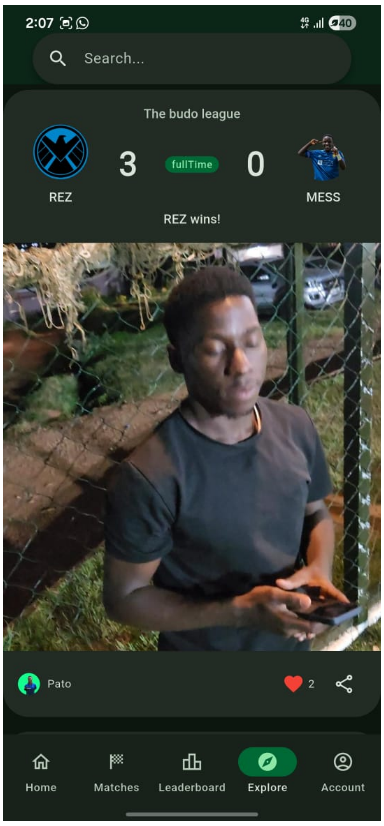

Figure G.2: Explore page in the application.

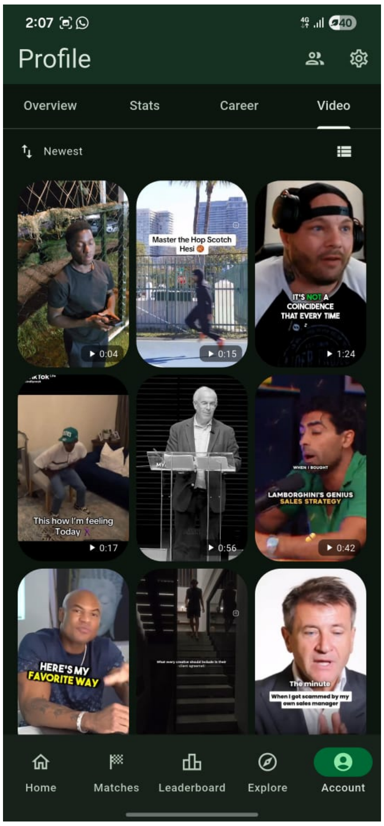

Figure G.3: Content page under different players' profiles.

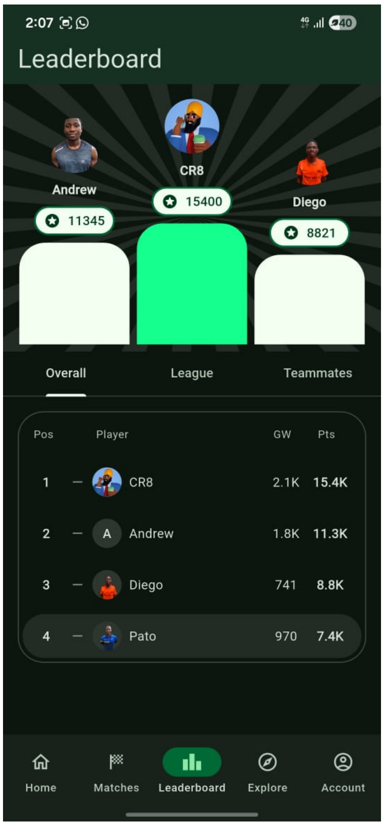

Figure G.4: Leaderboard to compare players.

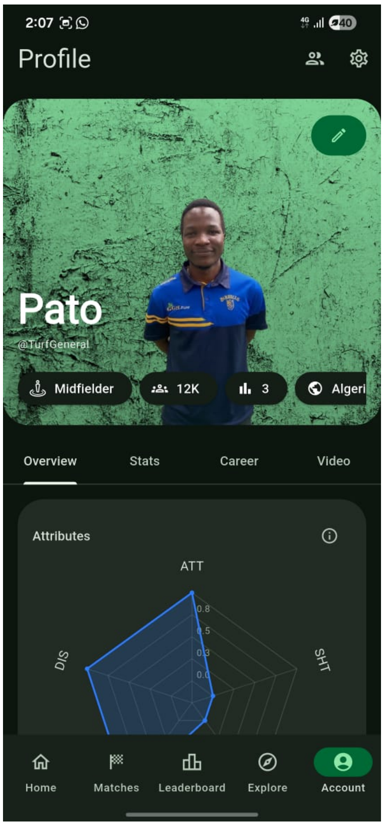

Figure G.5: Player profile page.

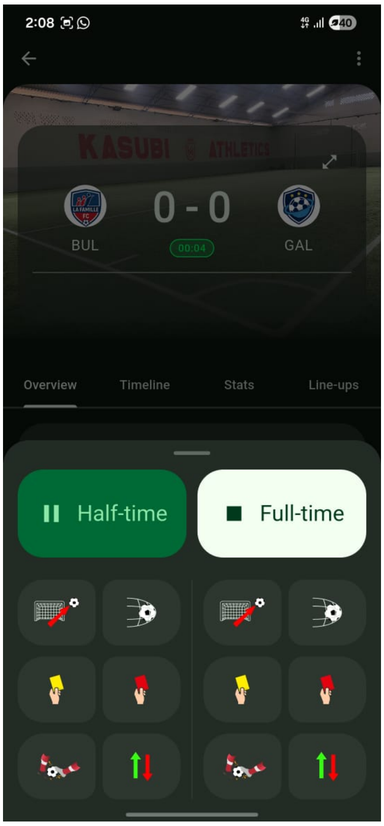

Figure G.6: Referee interface.

Appendix H

Research poster layout