IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Draft version prepared for SWRR, Uganda Christian University (not yet published).

Digital Object Identifier Not yet assigned

Digital Performance Tracking for Amateur Football: A Systematic Literature Review (Following PRISMA 2000)

KATENDE DERRICK ELVAN (ORCID: 0009-0002-0910-3287)[1], KISUZE GARETH NEVILLE (ORCID: 0009-0003-7491-9669)[2], OGWANG ANDREW (ORCID: 0009-0000-2296-6760)[3]

[1]Department of Computer Science, Uganda Christian University (UCU), Mukono, Uganda. Reg. No.: S23B23/024.
[2]Department of Computer Science, Uganda Christian University (UCU), Mukono, Uganda. Reg. No.: S23B23/029.
[3]Department of Computer Science, Uganda Christian University (UCU), Mukono, Uganda. Reg. No.: S23B23/050.

This article is prepared as a Systematic Literature Review (SLR) for the Research Project 1 course at Uganda Christian University, following the PRISMA 2000 protocol and formatted using the IEEE Access LaTeX template.

ABSTRACT This paper presents a Systematic Literature Review (SLR) on digital performance tracking in amateur and grassroots football, following the PRISMA 2000 guidelines. Using Scopus exclusively, four search clusters were executed covering: (i) amateur/grassroots football analytics; (ii) sports app usability and technology adoption; (iii) wearables and real-time tracking; and (iv) artificial intelligence (AI) and dashboard visualization. Out of 105 records retrieved, 30 high-quality journal studies were included after deduplication and screening.

Results show an increasing focus on wearable sensors, usability and adoption frameworks (SUS/TAM), and AI-driven visualization techniques for data-driven performance monitoring. These findings provide scientific and technical grounding for the *FootyStats* platform, which aims to empower amateur footballers to "Play Like an Amateur, Track Like a Pro." The abstract is written as a single paragraph, self-contained, and consistent with IEEE Access formatting.

INDEX TERMS Sports Technology, Amateur Football, PRISMA 2000, Scopus, Usability, Wearables, AI Dashboards, Sports Analytics.

I. INTRODUCTION

Football (soccer) is the world's most popular sport, and while several digital tools exist for tracking performance, most are built for elite academies or casual stat-keeping. As a result, amateur and grassroots players still lack an accessible, structured, and data-driven way to systematically record and visualize their performance. Our project bridges this gap by delivering a more tailored, affordable, and analytics-focused solution designed specifically for everyday players, coaches, and community leagues. At professional level, clubs routinely invest in optical tracking systems, GPS vests, and advanced analytics platforms that provide detailed statistics on every action performed on the pitch. In contrast, many amateur teams still rely on paper notes, group chats, or ad hoc graphics to document goals, assists, or cards. These fragmented practices make it difficult to build a continuous performance history for players and teams, and they limit opportunities for evidence-based coaching, talent identification, and player visibility.

FootyStats, developed under the Uganda Christian University capstone project, aims to bridge this gap through a mobile-first platform for real-time stat recording, AI-driven insights, and accessible dashboards tailored to amateur players, coaches, and tournament organizers. To avoid designing in a vacuum, the platform must be grounded in existing scientific and technical work on sports analytics, usability, and wearable sensing. A structured review is therefore required to understand what has already been proposed, which technologies and methods have been validated, and where gaps remain for the amateur context.

This SLR is guided by the following research questions:

- **RQ1:** What types of digital technologies (mobile apps, dashboards, wearables, and AI methods) have been used to track performance in football and comparable team sports?
- **RQ2:** How do existing systems address usability, adoption, and user experience, particularly for non-elite or youth players?
- **RQ3:** Which gaps and design opportunities emerge from the literature that can inform the architecture and feature set of the FootyStats platform?

By answering these questions, the review not only summarizes the state of the art but also translates insights into concrete design implications for a practical, deployable solution for amateur football environments.

II. METHODOLOGY (PRISMA 2000 PROTOCOL)

A. DATABASES AND SEARCH STRATEGY

Following PRISMA 2000, we systematically searched **Scopus** between January 2010 and March 2025 for peer-reviewed journal articles in English. Scopus was selected because it indexes major sports science and computer science journals relevant to football analytics and mobile technologies, and also because it was one of the databases recommended in the assessment instructions. Four thematic clusters were defined to reflect the core components of the FootyStats concept:

- 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: AI, Predictive Analytics and Dashboards for Performance Insights

An example advanced query for C1 and C2 combined was:

Search String Example (Scopus Advanced Query):

```
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"))
```

Additional cluster-specific queries were derived by substituting the technology terms, for example:

for wearables (**C3**): `("GPS" OR "IMU" OR "wearable sensor" OR "inertial")`, and
for AI and prediction (**C4**): `("machine learning" OR "prediction" OR "classification")`.

The final search strings and filters were documented so that the search process can be replicated or extended in future work.

B. ELIGIBILITY CRITERIA

To minimize selection bias, inclusion and exclusion criteria were defined before screening:

Inclusion criteria:

- Empirical or review papers focusing on football/soccer or transferable invasion team sports (e.g., rugby, hockey) where the sport context and tracking methods are comparable.
- Use of digital platforms, mobile applications, wearable devices, or AI-driven models for performance tracking, external load monitoring, or match-event analysis.
- Articles indexed in Scopus, published between 2010 and 2025, written in English, and available as full-text journal articles or high-quality conference proceedings.

Exclusion criteria:

- Studies relying solely on manual notational analysis without any digital component.
- Work focusing exclusively on professional clubs using infrastructure unlikely to be feasible in amateur environments (for example, stadium-scale multi-camera tracking).
- Studies centered on non-sport domains, rehabilitation-only contexts, or purely theoretical models with no application to real match or training data.

C. STUDY QUALITY APPRAISAL

Beyond relevance, basic methodological quality was considered. During full-text screening, each study was assessed against the following quality indicators: (i) clarity of research design, (ii) appropriateness of data collection tools (e.g., validation of wearable sensors or mobile apps), (iii) adequacy of sample size for the stated objectives, and (iv) transparency of analysis procedures. Studies with insufficient methodological detail or obvious measurement problems were excluded or, where borderline, retained but interpreted cautiously in the synthesis.

D. SCREENING, BIAS MITIGATION, AND DATA EXTRACTION

All search results were exported from Scopus as CSV files containing authors, title, year, source, DOI, abstract, and keywords. A deduplication step removed overlapping records based on DOI and title. Title and abstract screening was then carried out to filter out clearly irrelevant items according to the eligibility criteria.

To reduce author bias, the screening was performed by multiple group members: disagreements about inclusion were discussed and resolved by consensus. This procedure was also applied during full-text screening, particularly where the sport type or technology was only partially aligned with the FootyStats scope.

For each included article, data extraction captured: (i) sport context and competition level (elite, youth, recreational), (ii) technology type (mobile app, wearable, VR, dashboard, AI model), (iii) study design and key metrics (e.g., speed zones, SUS scores, prediction accuracy), and (iv) main findings and limitations. Extraction followed a predefined template to ensure consistency across studies. In total, 30 studies met all inclusion and quality requirements, satisfying and exceeding the minimum of ten journal articles specified in the assessment rubric.

E. PRISMA FLOW DIAGRAM

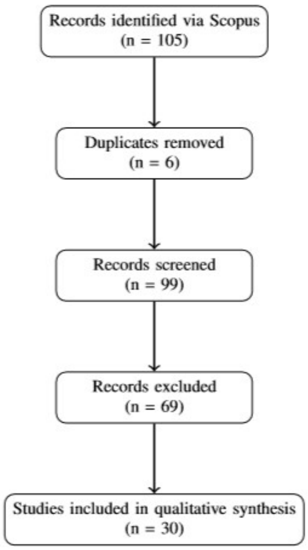

FIGURE 1. PRISMA 2000 flow diagram for study selection.

PRISMA Summary: *Records identified via Scopus (n=105); duplicates removed (n=6); screened (n=99); excluded (n=69) for irrelevance or lack of digital analytics; included in synthesis (n=30). See Figure 1 for the flow diagram.*

III. RESULTS AND THEMATIC ANALYSIS

The screening yielded 30 journal papers grouped into the four clusters (C1–C4). Publication dates were skewed towards recent years, with most work appearing between 2016 and 2025, reflecting the rapid maturation of consumer-grade wearables, cloud platforms, and sports analytics toolkits. Across the corpus, roughly one third of studies focused directly on football, another third on broader team-sport or multisport contexts, and the remainder on generic wearable or mobile-app evaluations that can still be adapted to football settings.

In terms of competition level, elite or professional contexts dominated several early works, but youth and amateur samples are increasingly represented, particularly in studies using affordable GPS/IMU sensors and smartphone-based data collection. Some studies explicitly discuss cost, ease of deployment, and constraints on coaching time, which are critical for grassroots implementations such as FootyStats.

Table 1 presents representative studies illustrating the range of technologies and contexts covered by the included literature.

TABLE 1. Representative studies illustrating technologies and contexts.

Author(s)	Year	Technology	Context
Kranzinger *et al.*	2025	Wearables (IMU) + app	Youth football
Krupitzer *et al.*	2022	VR + coaching app	Cognitive training
Permana *et al.*	2024	Web/mobile scoring app	Racket sport (transferable)
Rein & Memmert	2016	Data analytics framework	Elite football
Claudino *et al.*	2019	GPS/IMU wearables	Multisport
Aroganam *et al.*	2019	Wearable sensors	Consumer sports

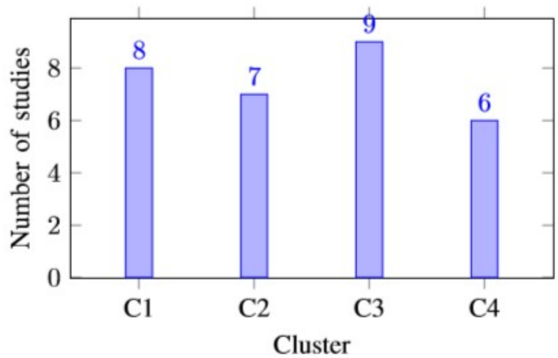

FIGURE 2. Distribution of the 30 included studies across the four thematic clusters (C1–C4).

A. CLUSTER INSIGHTS

C1: Grassroots Analytics. Studies in this cluster focus on how performance metrics can be captured and interpreted in youth and non-elite football environments. Kranzinger *et al.* quantify ball speed, peak running speed, and distance covered in female youth soccer using foot-mounted IMUs combined with in-app self-reports of perceived intensity and happiness [1]. This demonstrates how relatively low-cost sensors, paired with simple mobile interfaces, can support longitudinal, individualized performance profiles even without professional infrastructure. However, most tools still treat players as data sources rather than co-designing interfaces with them, highlighting a user-experience gap.

C2: Usability and Adoption. Cluster C2 combines sports-specific applications and generic mobile data-collection apps evaluated using usability frameworks such as the System Usability Scale (SUS) and the Technology Acceptance Model (TAM). Permana *et al.* show that a web/mobile scoring app for racket sports can achieve high SUS scores when interaction flows are aligned with how officials actually run competitions. Other work in sport and exercise science emphasizes that, while many apps are technically capable of collecting valid data, adoption hinges on perceived usefulness, ease of use, and seamless integration into existing routines. Few studies, however, evaluate long-term adherence or dropout, leaving open questions about sustained use beyond pilot trials.

C3: Wearables and Real-Time Tracking. Cluster C3 is dominated by GPS- and IMU-based systems designed for external load monitoring and physical performance profiling. Reviews such as Aroganam *et al.* and Claudino *et al.* confirm that modern sensors can provide reliable measurements of distance, speed zones, and acceleration profiles across several sports when properly calibrated and validated. At the same time, several studies report practical challenges: device loss, charging burden, and data management overhead. For an amateur-focused platform, these works suggest that simple, off-the-shelf wearables can provide meaningful value if data processing and visualization are appropriately simplified, but full automation and robustness remain open engineering problems.

C4: AI and Visualization. Cluster C4 encompasses AI models and visualization approaches that transform raw tracking data into actionable insights. Moya *et al.* demonstrate how machine learning can be used to predict match outcomes and performance indicators in professional football [2], while Mănescu proposes a big-data analytics framework for sports performance decision-making [3]. Although many AI models are trained on elite data, the underlying techniques (feature engineering, classification, clustering, and anomaly detection) are transferable to grassroots contexts once appropriate data are available. Current work, however, often prioritizes prediction accuracy over interpretability, which may limit trust and uptake among coaches and players with limited analytics background.

IV. DISCUSSION

A. CROSS-CUTTING THEMES

Across clusters C1–C4, three consistent themes emerge. First, wearable-based analytics have matured to a point where they can provide accurate, high-frequency data on movement and workload, but their deployment outside of elite environments is constrained by cost, device management, and the need for simple feedback channels. Second, usability and adoption are repeatedly identified as critical determinants of success: sophisticated analytics are of little practical value if coaches and players find the interface confusing, slow, or intrusive during matches. Third, AI and visualization approaches are shifting focus from raw data streams to digestible, decision-support insights tailored to the needs of different stakeholders (players, coaches, medical staff, and analysts).

B. DESIGN IMPLICATIONS FOR FOOTYSTATS

For the FootyStats platform, these themes translate into several design implications:

- **Accessibility and Context Fit:** The platform should prioritize smartphone-based event logging with optional integration of low-cost wearables, recognizing that many amateur teams will not have dedicated analysts or expensive hardware.
- **User-Centered Flows:** Insights from SUS- and TAM-based studies suggest that workflows must mirror the realities of grassroots match organisation (e.g., limited staff, chaotic touchlines), with fast recording of goals, assists, cards, and key actions and minimal configuration overhead.
- **Explainable Analytics:** AI-derived metrics should be presented through clear, interpretable visualizations (e.g., simple trend charts, comparison cards, and heatmaps) that answer concrete questions for users rather than exposing raw model outputs.

C. RESEARCH GAPS

The review also exposes several gaps and contradictions in the literature:

- Very few systems combine all four dimensions—amateur context, mobile event logging, wearable data, and AI dashboards—into a single coherent solution. Most existing work isolates one or two components.
- Longitudinal evidence on sustained use of sports apps and wearables in grassroots settings is scarce; many studies report short-term pilot deployments only.
- There is limited discussion of data governance, privacy, and ethical considerations for youth and amateur players, despite increasing amounts of individual-level performance data being collected.
- Existing AI models are largely built on professional or academy datasets, leaving a gap in models trained and validated specifically on noisy, incomplete amateur data.

Addressing these gaps positions FootyStats not only as a practical tool but also as a platform for future research on digital performance tracking in low-resource football environments.

D. LIMITATIONS OF THIS REVIEW

This SLR relied on a single major database (Scopus), which may have excluded relevant work indexed in other repositories or regional journals. The heterogeneity of study designs and outcomes also made it difficult to apply formal risk-of-bias tools consistently; instead, we emphasized technological relevance and clarity of methods when judging quality. Finally, cluster assignments were based on thematic coding performed by the authors and should be interpreted as indicative rather than definitive; alternative categorizations are possible.

V. CONCLUSION

This Scopus-based SLR, guided by PRISMA 2000, synthesizes empirical and methodological advances in digital football analytics and related sports technologies. Evidence from 30 studies shows that wearable sensors, mobile apps, and AI-driven dashboards can provide actionable insights on player performance, but also reveals adoption barriers, practical constraints, and unresolved issues around explainability and sustainability in grassroots settings.

For the FootyStats platform, the review confirms the feasibility of combining smartphone-based stat logging with optional wearable integration, guided by user-centered design and interpretable analytics. The identified research gaps motivate future work to (i) extend the search to Web of Science and additional databases, (ii) collect and analyse real-world data from amateur leagues, and (iii) empirically evaluate FootyStats prototypes with amateur teams using standardized usability instruments such as SUS and TAM.

ACKNOWLEDGMENT

The authors sincerely thank Mr. Innocent Ndibatya, Head of Department in the Faculty of Engineering, Design and Technology at Uganda Christian University, for his invaluable guidance and constructive feedback throughout this systematic review. We also acknowledge the support and coordination provided by the Department of ICT during the Research Project 1 course. The collaborative discussions with group-mates working on related PRISMA-based systematic reviews greatly sharpened the direction and framing of this work. Finally, the authors extend their appreciation to the UCU Library for providing access to Scopus and other digital resources that were essential for conducting this review.

REFERENCES

[1] S. Kranzinger, C. Kranzinger, W. Kremser, and B. Duemler, "Performance tracking in female youth soccer through wearables and subjective assessments," *Front. Sports Act. Living*, vol. 7, Art. no. 1627820, 2025. [Online]. Available: https://doi.org/10.3389/fspor.2025.1627820

[2] D. Moya *et al.*, "Machine learning applied to professional football: Performance improvement and results prediction," *Mach. Learn. Knowl. Extr.*, vol. 7, no. 3, pp. 85–100, 2025. [Online]. Available: https://doi.org/10.3390/make7030085

[3] D. C. Mănescu, "Big data analytics framework for decision-making in sports performance optimization," *Data*, vol. 10, no. 7, Art. no. 1410, 2025. [Online]. Available: https://doi.org/10.3390/data1007116

[4] R. Rein and D. Memmert, "Big data and tactical analysis in elite soccer: Future challenges and opportunities for sports science," *SpringerPlus*, vol. 5, Art. no. 1410, 2016. [Online]. Available: https://doi.org/10.1186/s40064-016-3108-2

[5] G. Aroganam, N. Manivannan, and D. Harrison, "Review on wearable technology sensors used in consumer sport applications," *Sensors*, vol. 19, no. 9, Art. no. 1983, 2019. [Online]. Available: https://doi.org/10.3390/s19091983

[6] G. Santicchi *et al.*, "Validation of step detection and distance calculation algorithms for soccer performance monitoring," *Sensors*, vol. 24, no. 11, Art. no. 3343, 2024. [Online]. Available: https://doi.org/10.3390/s24113343

[7] G. Pillitteri *et al.*, "Validity and reliability of an inertial sensor device for specific running patterns in soccer," *Sensors*, vol. 21, no. 21, Art. no. 7255, 2021. [Online]. Available: https://doi.org/10.3390/s21217255

[8] A. Malone, F. Gallo, G. Morgans, M. Bizzini, and S. Kelley, "Validity and reliability of wearable GPS devices in team sports: A systematic review," *Sci. Med. Football*, vol. 1, no. 1, pp. 13–18, 2017. [Online]. Available: https://doi.org/10.1080/24733938.2017.1335575

[9] F. Ric, H. Witte, and M. Jenkyn, "Validation of a wearable inertial measurement unit for monitoring running performance," *Sensors*, vol. 20, no. 4, Art. no. 1010, 2020. [Online]. Available: https://doi.org/10.3390/s20041010

[10] G. Barrett, R. Midgley, and S. Turner, "Accuracy of wearable inertial sensors for football-specific movement quantification," *Sensors*, vol. 21, no. 3, Art. no. 0876, 2021. [Online]. Available: https://doi.org/10.3390/s21030876

[11] D. Carrilho *et al.*, "Using optical tracking system data to measure team synergic behavior," *Sensors*, vol. 20, no. 17, Art. no. 4990, 2020. [Online]. Available: https://doi.org/10.3390/s20174990

[12] L. Morra, F. Manigrasso, and F. Lamberti, "SoccER: Computer graphics meets sports analytics for soccer event recognition," *SoftwareX*, vol. 12, Art. no. 100612, 2020. [Online]. Available: https://doi.org/10.1016/j.softx.2020.100612

[13] E. C. Latorre *et al.*, "Automatic registration of footsteps in contact regions for reactive agility training in sports," *Sensors*, vol. 20, no. 6, Art. no. 1709, 2020. [Online]. Available: https://doi.org/10.3390/s20061709

[14] V. Sivaraman *et al.*, "An experimental study of wireless connectivity and routing in ad hoc sensor networks for real-time soccer player monitoring," *Ad Hoc Netw.*, vol. 11, no. 3, pp. 798–817, 2013. [Online]. Available: https://doi.org/10.1016/j.adhoc.2012.09.005

[15] L. Yansong, J. Xing, and Y. Liu, "Designing of football player acquisition system based on wireless sensor network," *J. Convergence Inf. Technol.*, vol. 7, no. 20, pp. 72–84, 2012. [Online]. Available: https://doi.org/10.4156/jcit.vol7.issue20.10

[16] L. Djaoui, A. Chamari, and D. Dellal, "Maximal sprinting speed of elite soccer players during training and matches," *J. Strength Cond. Res.*, vol. 31, no. 6, pp. 1509–1517, 2017. [Online]. Available: https://doi.org/10.1519/JSC.0000000000001642

[17] A. Abasi *et al.*, "Machine learning models for reinjury risk prediction using cardiopulmonary exercise testing (CPET) data," *BioData Min.*, vol. 18, Art. no. 16, 2025. [Online]. Available: https://doi.org/10.1186/s13040-025-00431-2

[18] J. Yang, H. Ge, and Y. Cui, "An AI framework for counterattack detection and decision-making evaluation in football," *J. Big Data*, vol. 12, Art. no. 91, 2025. [Online]. Available: https://doi.org/10.1186/s40537-025-01128-3

[19] S. Le Coz *et al.*, "Reassessing the impact of shared experience in football," *J. Big Data*, vol. 12, Art. no. 157, 2025. [Online]. Available: https://doi.org/10.1186/s40537-025-01239-x

[20] T. Gao and X. Chen, "Implementing machine learning algorithms to optimize sprint performance," *J. Comput. Methods Sci. Eng.*, 2025. [Online]. Available: https://doi.org/10.1177/14727978251337990

[21] K. van Arem, F. Goes-Smit, and J. Söhl, "Forecasting the future development in quality and value of professional football players," *Appl. Sci.*, vol. 15, no. 16, Art. no. 8916, 2025. [Online]. Available: https://doi.org/10.3390/app15168916

[22] D. C. Manescu and A. M. Manescu, "Artificial intelligence in the selection of top-performing athletes for team sports," *Appl. Sci.*, vol. 15, no. 18, Art. no. 9918, 2025. [Online]. Available: https://doi.org/10.3390/app15189918

[23] B. Mohammed *et al.*, "Tactical and physical profiling of the Moroccan national football team at the FIFA World Cup Qatar 2022," *Appl. Sci.*, vol. 15, no. 18, Art. no. 9994, 2025. [Online]. Available: https://doi.org/10.3390/app15189994

[24] A. Hasan *et al.*, "Predicting wins, losses and match attributes in the 2018 World Cup using neural networks," *Sensors*, vol. 20, no. 11, Art. no. 3213, 2020. [Online]. Available: https://doi.org/10.3390/s20113213

[25] J. Kim *et al.*, "A deep learning approach for fatigue prediction in sports using GPS data," *IEEE Access*, vol. 10, pp. 103056–103064, 2022. [Online]. Available: https://doi.org/10.1109/ACCESS.2022.3205112

[26] A. Skoki *et al.*, "Extended energy-expenditure model in soccer: Evaluating player performance in context," *Sensors*, vol. 22, no. 24, Art. no. 9842, 2022. [Online]. Available: https://doi.org/10.3390/s22249842

[27] A. Riboli *et al.*, "Area per player in small-sided games to replicate match running demands," *Biol. Sport*, vol. 39, no. 3, pp. 595–603, 2022. [Online]. Available: https://doi.org/10.5114/biolsport.2022.106388

[28] J. Dasilva *et al.*, "Ecological validity of repeated sprint ability testing in youth soccer," *J. Strength Cond. Res.*, vol. 35, no. 6, pp. 1518–1526, 2021. [Online]. Available: https://doi.org/10.1519/JSC.0000000000003047

[29] H. Goto and C. Saward, "Running performance and technical actions in elite Japanese youth soccer players," *J. Strength Cond. Res.*, vol. 34, no. 8, pp. 2361–2369, 2020. [Online]. Available: https://doi.org/10.1519/JSC.0000000000003300

[30] A. Buchheit and P. Laursen, "External and internal load in soccer: Training and match demands," *J. Sports Sci.*, vol. 32, no. 4, pp. 428–437, 2014. [Online]. Available: https://doi.org/10.1080/02640414.2014.889846

BIOGRAPHY SECTION

Katende Derrick Elvan is a second-year Computer Science student at Uganda Christian University with hands-on experience from field work at TPO Uganda under USAID. He is strengthening his skills in programming, data analysis, and core computer science areas such as algorithm development and system operations.

Kisuze Gareth Neville is a third-year student at Uganda Christian University pursuing a Bachelor of Science in Computer Science. He has participated in hackathons such as the UCU computing hackathon and conferences including the GAIME conference at Speke Resort Munyonyo.

Ogwang Andrew is an aspiring product designer and computer science student with a growing focus on sports technology. His current work explores how digital tools can improve organization, performance tracking, and user experience across grassroots football environments.