Final Year Project

Name: Kayla O Riordan

Title: How advanced performance monitoring devices contribute to analysing behavioural impacts and enhancing performance in GAA.

Supervisor: Pedro Nilsson-Fernàndez

BA Digital Humanities & Information Technology

April 2024

Table of Contents

Abstract

This research project investigates the impact of advanced performance monitoring technologies on social dynamics and athletic performance within Gaelic Athletic Association (GAA) sports, focusing on data collected from October to March. The primary objective of this research is to examine the relationship between the performance devices and the players psychological effects.

Furthermore, the study examines the psychological impacts of these technologies, particularly in terms of players' feelings of community belonging, team morale, and social inclusion. A survey was conducted to gather insights into players' perceptions of their communities, aiming to uncover the complex relationships between athletic performance, social dynamics, and community engagement.

By integrating quantitative performance data with qualitative insights from player perceptions, the research seeks to determine if there are any correlations between these two dimensions. This approach aims to provide a comprehensive understanding of the technological impacts on team dynamics and individual athletic performance.

Introduction

There is a strong appreciation for the excellence that comes from athletic ambition that exists within the competitive environment of sports, where teams and athletes strive for constant improvement and success. From an athlete's perspective there's more to sports than just collecting trophies and awards, there's the passion for the sport, which can be seen by the movement of a skilfully performed sport, the unspoken cooperation and team spirit among teammates, and the persistent determination of athletes. Over the recent years, the introduction of technology has revolutionized the way athletic performance is monitored and analysed. The widespread use of technology has led to a lack of understanding of its impact and the role it plays in sports (Omoregie, P.O., 2016). This research project aims to examine advanced performance monitoring technologies and their use in Gaelic Athletic Association (GAA) sport. The objective of this research is to thoroughly examine the impact of these technologies on athletic performance and on the social dynamics among athletes.

The primary research question of this project seeks to answer how these advanced performance monitoring devices have an impact on athletes' perceptions on performance, motivation, team morale and sense of community belonging. By researching these areas, this study hopes to provide an integrative perspective on the technical and social benefits of modern sports technology.

To conduct this research, a mixed-methods approach is used, combining quantitative data from performance metrics with qualitative data from player surveys. This method offers an in-depth analysis of technological impacts, allowing for a detailed examination which takes advantage of both statistical data and personal player experiences. The quantitative aspect of the study involves data gathering and analysis using an advanced wearable performance monitor called Statsport. These sensors record a variety of parameters throughout training and matches, including distance travelled, speed, and acceleration. In addition to the quantitative data, qualitative insights are gathered through a survey that look into athletes' perceptions of their performance, the psychological influence of monitoring devices. These surveys aim to uncover deeper socio-psychological aspects that are associated with physical performance, such as motivation, mental toughness, and the sense of performance pressure from both the community and the team.

The practical outcome of this project is the creation of a digital artefact. For this, an interactive visualisation dashboard was developed, which integrated and visually represented the data collected. This artefact serves not only as a method for providing feedback from training sessions and matches, but also as a long-term monitoring and analysis platform.

To summarise, this research tries to bridge the gap between developments in technology and practical application in sports. It intends to show how advanced monitoring might help determine a better understanding of the intricate relationship between physical performance and their psychological attitudes in the sport.

Literature review

This literature review aims to understand how advanced performance monitoring devices contribute to analysing behavioural impacts and enhancing performance in GAA. As a result of developments in data analytics, wireless networking, and sensor technologies, monitoring devices have evolved significantly over time. A monitoring device can be defined as a small electronic equipment, able to collect data from some on-board sensors and perform simple elaborations on them in order to extract meaningful output data (Iervolino., 2017). Performance monitoring in GAA is crucial for many reasons. Hurling and Gaelic football require a combination of physical fitness, skill, and strategic play. Feedback is the most important variable for learning, modern technical equipment can help both the performer and the instructor by providing additional, parallel feedback information that is not obtainable by traditional observation methods (Kos et al., 2018).

Performance monitoring

With the advancement of technology, the variety and quality of equipment used in the sports environment has increased (AK, M.O., 2021). The development of new sensor technology enables us to investigate those incremental improvements, and as the technology continues to evolve, our ability to analyse and comprehend them expands significantly (Berg et al., 2023).

It is said by Rana, M. and Mittal, V., (2020) that wearable technology, particularly IMUs, has revolutionized the way performance analysis is conducted in sports. Initially developed for advanced data acquisition in sports, IMUs now facilitate the extraction and analysis of performance and kinematics metrics, driven by significant advancements in sports analytics and data fusion techniques. Demonstrating their accuracy, a study on young football players using the latest generation IMUs provided highly precise data, successfully capturing detailed performance indices related to body symmetry and dynamic balance during directional changes, thereby validating their utility in sports science (Izzo et al., 2022). However, Arlotti, J.S. (2022) highlights while IMU based wearables shown promise, there are still barriers to overcome for future implementation. Many of the IMU sensor solutions require a level of setup or calibration that is unreasonable given the expertise level of some general consumers. Addressing these challenges is crucial for the future of wearable sports technology. Previous research showed by Seçkin et al., (2023) suggest that despite existing challenges, there is a promising future for wearable technology in sports. The article's emphasis on future research supports the notion that overcoming current barriers could lead to broader adoption and greater utility of IMU-based wearables in sports.

In sports games, when a comparison of physical demands is required according to changes in distance, speed, and acceleration on different playing surfaces, monitoring and measurement using GPS is very suitable. (Bădescu et al., 2022). It is also stated by Memmert, D. and Rein, R., (2018) that GPS tracking becomes an essential feature that provides greatly to the amount of positional data that can be analysed. The emphasis on the reliability and validity of positional data highlights the importance of GPS technology in capturing players' movements on the field. This real time tracking enables the ability to assess distance covered and in real time during training and matches provides a comprehensive overview of an individual's fitness levels and workload.

Combined IMU and GPS data have been used to obtain sensitive and holistic measures of external loading in team sports. Specifically, they enable the detection of abrupt changes in running velocity and direction, as well as impact identification and classification. (Camomilla et al., 2018). Furthermore, in a study carried out by Waegli et al., (2008), it was discovered that the integration of GPS with redundant MEMS-IMUs leads to a significant improvement in navigation performance. Using geometries like skew redundant IMUs placed on the faces of a regular tetrahedron, navigation performance can be enhanced by 30-50%, and maximum errors can be reduced by a factor of 2.

Sensors that determine physiologic response to changes in competition and training are also crucial in promoting improved performance and decreased injury. Heart rate is a useful indicator of physiological adaptation and intensity of effort. (Li et al., 2016). As well as this, it is suggested that longitudinal monitoring is required to understand each athlete's optimal HRV to R–R interval fingerprint because it is clear that HRV responses are individual and dependent on fitness level and training history. (Plews et al., 2013).

Individual and team performance

There is a growing trend in the athletic and health care environment to monitor human physiologic function and performance during real-time activities. (Li et al., 2016). Metrics can be very informative and indicative for coaches and training staff to get a better understanding of each individual player and the roster as a whole, along with increases or decreases in their abilities, strength, and readiness (Ravindranathan et al., 2017). Researchers have noted that Gaelic games players could be particularly susceptible to burnout due to the intense demands of balancing work, life, and playing Gaelic games (Woods et al., 2020). The study of the human motion is based on the variables which describe the kinematics and the dynamics of the anatomic segments, i.e. displacements, velocities and accelerations, which are fundamental for any accurate classification as required in the analysis of sport performance (Iervolino, R., Bonavolontà, F. and Cavallari, A., 2017). The capacity to collect and analyse vast datasets on athlete performance and strategic planning has significantly grown, Rein, R. and Memmert, D., (2016) emphasize that this analytical prowess is pivotal for optimizing both individual performance and broader organizational strategies. Neville, J., Wixted, A., Rowlands, D. and James, D., (2010) argue that in order for an individual or team to improve it is required to assess how well the athlete or team are adapting to training and match loads. This concept is further supported by Akenhead, R. and Nassis, G.P., (2016) who emphasize that training load is monitored with the aim of making evidence-based decisions on appropriate loading schemes to reduce injuries and enhance team performance. (Akenhead, R. and Nassis, G.P., 2016). However, not all performances can benefit from the implement these monitoring systems. According to Halson, S.L. (2014), obstacles such a lack of resources including the time, money, and labour required to gather, process, and analyse data, can impede the implementation of such systems. Despite these challenges, there are successful examples where continuous monitoring has significant benefits. For instance, Camomilla et al., (2018) demonstrated how continuous monitoring during training sessions could capture real-time data that was instantly analysed to provide immediate feedback, enhancing training efficiency. Similarly, a study by Rabbani, A., Kargarfard, M. and Twist, C., (2020) emphasizes the value of distinguishing between group and individual monitoring of fitness using submaximal tests in elite soccer players. They found that while group analyses often show trivial changes, individual data can reveal substantial differences in responses to training loads, highlighting the critical role of tailored monitoring strategies in optimizing performance and readiness."

Practitioners often collect a plethora of athlete monitoring data in relation to external and internal TL, fitness and fatigue that can illuminate whether athletes are adapting to their training programs, or whether they are at risk of overtraining, and an elevated potential for injury. (Duggan et al., 2021). An athlete's overall performance, durability in the sport, and general health are all impacted by their training loads and injury prevention methods. In addition to increasing performance, a well-planned and executed training programme lowers the risk of injury, allowing athletes to push themselves in the right direction of long-term success.

Psychology

Since this research includes a survey that questions players' opinions, psychology in sports is extremely important for this project. Athletes' success is not solely dependent on physical abilities but also on their mental preparation (Kolt, G.S., 2015). A number of authors have recognized that there is a significant relationship between sports and psychological well-being. It is suggested by Mammen, G. and Faulkner, G., (2013) that consistent physical activity can serve as a preventative measure against depression. Furthermore, the results of a study on the mental health of GAA players by Lee, C., (2019) found a significant difference in depression scores between college students and those who were not in college, with college students exhibiting higher levels of depression. This result supported the hypothesis that college students would have higher depression scores due to the pressures of managing both academic responsibilities and GAA commitments.

In research carried out by Ribeiro et al., (2023) well-being scores were collected using subjective self-assessment questionnaires that players completed and used to evaluate players' readiness and overall state throughout the training and competitive phases. The study found that higher well-being scores, which indicate better recovery and lower stress levels, were associated with lower variability in neuromuscular performance. This suggests that when players reported feeling better overall, their performance tended to be more consistent. Although Ribeiro et al., (2023) did not directly measure psychological readiness or mental health variables beyond those included in the well-being scores, Gallagher, L., (2019) employed online surveys that included the Sports Mental Toughness Questionnaire (SMTQ) and the Depression, Anxiety, Stress Scale (DASS-21). There was a statistically significant negative correlation between mental toughness and mental health issues, indicating that players with higher mental toughness experienced lower levels of depression, anxiety, and stress. An improvement to any single physiological or psychological parameter could potentially give one athlete a 'winning edge' over his or her competitors" (Ride et al., 2013). Although these evaluations offer insightful information, they are not as precise and fast as real-time data collection. A platform developed Bailon et al., (2018) offers a promising solution to these studies limitations. This method allows for the continuous and real-time monitoring of athletes' affective states through the integration of data from wearable sensors and smartphones. In addition to capturing the dynamic aspect of psychological states, this technology provides a more accurate measurement that is less prone to the biases of self-report methods.

According to Ryan et al., (2019), using wearable technology contributes to complex behavioural dynamics. Results show that while wearing their devices, users typically feel confident, motivated, and accountable, however there was a notable presence of negative emotions such as frustration and anxiety related to dependency on the technology for emotional satisfaction and self-esteem for not accomplishing what their goals. Further evidence provided by Samełko et al., (2018) supports the notion that affective states influence performance outcomes. Nonetheless, it is underscored that there is significant variability among individuals regarding which emotional states are optimal for performance. This variability means that what works for one athlete in terms of emotional preparation may not work for another (Hanin, Y.L., 2003).

Community

As the project's survey includes questions about community, it is critical to understand the influence it plays in player perceptions. Previous studies have examined the relationships between athletes and their communities. Recent evidence found by Keane, J., (2001) has suggested that hurling and participation in the G.A.A. club strengthen local identities and the concept of place. It is evident in the strong emotional attachments to the club, which serves not only as a social hub but also as an anchor of communal identity. Members feel a sense of pride and belonging as a result of the club's activities, which preserve local boundaries and distinctions. A study conducted by Eime et al., (2013) provides deep research evidence about the positive effects of sports engagement on social health, which is in agreement with the findings made by Keane, J., (2001) about G.A.A. clubs. It is discovered that participating in sports is often associated with better social health outcomes, such as improved interpersonal skills and a stronger sense of community. Moreover, Brown, K.M., Hoye, R. and

Nicholson, M., (2014) uses a mixed-methods approach to show how playing sports can help to develop a sense of community and trust by mixing qualitative interviews with quantitative surveys. This research highlights the value of sports in building greater socialisation and trust as well as bringing people together, which strengthens a community's sense of connection and belonging.

Interventions in sports play a role in fostering community support and guaranteeing athletes' continued participation. Eime et al., (2008) provides comprehensive insights into various interventions aimed at promoting health and inclusivity within sports clubs. The goal of these programmes is to change sports clubs from being simply athletic facilities into social spaces where members can find support, friendship, and a sense of purpose. Lavallee et al., (2019) makes a similar point in his study examining how targeted social support systems can dramatically decrease dropout rates among youth athletes. According to the study, young athletes who receive regular, encouraging feedback from their coaches, friends, and families are more likely to stay motivated and involved in sports and physical exercise throughout their lives. Both studies show that sports interventions are capable of helping communities in ways that go beyond mere participation.

Environmental scan

These resources will give a broad view of how modern technology is being integrated into sports and how these innovations can apply to enhance the performance monitoring aspects of the research project.

Current Practices and Their Limitations

The study conducted by Cullen et al. (2021) provides critical insights into current athlete monitoring practices. It demonstrates the ecological validity of self-reported wellness metrics in measuring athletes' readiness for training and competition. While this method offers a foundation for assessing athlete readiness, it also has notable limitations, particularly its reliance on subjective data. All of this sets a framework for this research, which aims to not only gather subjective wellness data but also enhance it with objective performance metrics.

Technological Advancements in Athlete Monitoring

Transitioning from traditional monitoring techniques, the article by Flynn (2023) discusses the evolution of wearable technology, including fitness trackers and GPS sensors. These technologies offer real-time, quantitative data that can significantly enhance and improve the qualitative data collected through the survey. The development in wearable technology aligns with the project's objectives, allowing a more thorough and accurate assessment of athlete performance and readiness which directly addresses the limitations highlighted by Cullen et al.

The Role of Mixed Methods in Enhancing Data Analysis

The approach recommended by Camerino et al. (2012) in "Mixed Methods Research in the Movement Sciences" builds on the integration of advanced technology and encourages the use of both quantitative and qualitative data. This methodology is particularly useful for this project as it provides an accurate structure for analysing the diverse data sets gathered from wearable technology and psychological assessments.

Incorporating Psychological Aspects into Performance Monitoring

Moreover, the systematic review by Reyes-Bossio et al., (2022) emphasizes the impact of psychological interventions of high performance athletes. It highlights the importance of considering psychological factors alongside physical data, which supports the projects comprehensive approach to athlete monitoring. By integrating psychological assessments indirectly through self-reports and directly through data analytics from wearable devices, the project provides a comprehensive approach that considers the mental well-being of athletes as an important component of performance enhancement.

Conclusion

While existing studies leverage either quantitative device data or qualitative self reporting. There is notable gap in research that integrates these two forms of data comprehensively to get a better understanding of how monitoring technologies influence both the physical and psychological dimensions of athletic performance. This research will aim to gather further insight to bridge these gaps by implementing a mixed methods approach using objective performance data with subjunctive survey responses.

Methods, tools and design

Research design

Overview

After considering various research possibilities, including the use of personal data from personal football training sessions, the idea was expanded to include cooperation between current teammates. The idea was to encourage teammates who wore fitness trackers during their sessions to share their data so that data could be analysed as a group, thereby creating a collective dataset for analysis. The objective of this methodology was to not only integrate the personal training data but also use other people's participation to enhance the dataset. However, unexpected challenges occurred when bad weather and pitch maintenance problems caused training sessions to be rescheduled, making it impossible to collect the needed data. Despite these obstacles the original concept opened up new possibilities for research, which resulted in this current project, which is focused on obtaining data from a senior level GAA squad. Additionally, this GAA team used more advanced technologies than originally anticipated which created an unexpected opportunity. This use of the latest technology improves the research's focus and allows for a more thorough analysis of how performance monitoring devices affect social dynamics within the GAA club as well as physical performance. The transition to the new project idea not only presented an opportunity for a fresh research direction but also sparked a wave of new ideas, which was to explore the complex relationship between social dynamics, athletic performance, and performance monitoring devices in the context of GAA. The methodical approach used to examine these various aspects is essential for this project. To successfully meet the study objectives, a mixed methods technique that integrates both quantitative and qualitative methodologies was chosen.

Firstly, an essential part of evaluating different performance data collected by performance monitoring equipment was the quantitative approach. With the help of this method, numerical data could be carefully analysed to find trends, patterns, and correlations that were relevant to athletic performance. This approach allowed for an evaluation of performance changes over time and comparisons across various conditions by using statistical techniques. Additionally, the quantitative analysis offered an organised structure for examining large amounts of data gathered from several training sessions and matches, offering a strong foundation for understanding how these devices affect athlete performance.

This study also aimed to investigate the psychological effects of using performance monitoring devices, specifically on motivation, social inclusion, and team morale. A survey was created to gather detailed, descriptive information on the personal perspectives and opinions of GAA players about their use of these devices as a way help achieve this objective. By gathering qualitative insights into player attitudes, beliefs, and behaviours, the aim was to provide insight into the complex dynamics behind the psychological impacts of performance monitoring technologies on the team.

Sampling

The sample group chosen for this research project were members of the Newmarket GAA team, a community strongly involved in GAA culture. Having personal involvement within the GAA community had a great benefit for the recruitment efforts as it assisted with connecting with the team's management. Given the personal involvement in GAA this also created an encouraging recruiting atmosphere and secured the teams participation. Regarding participant characteristics, the sample was composed of male athletes in the age range of 22 to 30 years. The team was selected based on their involvement in GAA activities, which makes them perfect for providing insights on their use of these monitoring devices are used in their training sessions and matches.

A total of 20 participants were recruited for the study, each meeting the specific participation requirements. These requirements included being a current member of the men's GAA team from Newmarket, completing the survey prepared, and having to be willing to share performance data from matches and training sessions.

Each participant was required to fill out the survey for the purpose of this research, information about the study's objectives and requirements was provided to potential participants, emphasizing the voluntary nature of participation. This open approach encouraged the participants to feel comfortable enough to openly discuss their experiences.

Participants were chosen through purposeful sampling according to their ability to provide helpful feedback on the research topic, this method of sampling is widely used in qualitative research for identification and selection of information (Palinkas et al., 2015). By carefully choosing participants with personal knowledge and experience relevant to the study's goals, this sampling strategy improved the study's legitimacy and relevance to the GAA community. The meticulous process of sample selection which consisted of purposeful sampling and recruitment through personal contacts and team management, made sure that the formed sample was in an advantageous position to make a significant contribution to the study.

Data collection strategy

This study was carried out in a longitudinal approach over a specific duration, between November and March. This time frame was strategically chosen to capture a representative sample of the team's performance dynamics across different phases of the GAA season, including preseason preparation, regular season fixtures, and championship matches.

This research's data gathering strategy used a combination of methods to capture participant qualitative insights as well as quantitative measurements of performance. This section describes the data collection methods used, which includes managing a survey and the use of performance monitoring devices.

The quantitative data for this study was obtained through a process of recording various performance metrics during training sessions and matches using monitoring device called STATsports, a compact GPS tracker is worn tucked into the Apex performance vest and avoids difficulties to players' movements while providing comprehensive data on many performance metrics. STATSports is the latest performance monitoring device equipped with advanced GPS tracking technology designed to provide comprehensive insights into athlete performance during training sessions and matches. It is the device Newmarket GAA work with to accurately capture their players movement, including distance covered, speed, acceleration, deceleration, and changes in direction. "Reliability was suitable and consistent for measures of distance, velocity, and average acceleration. STATSports devices generally possessed suitable reliability and consistency for threshold-based accelerations and decelerations." (Crang et al., 2022). The system gives a unique profile to every player, which makes it easier to manage workload and track metrics for performance on an individual.

These devices were crucial in generating a large data set that provides insightful information about the physical requirements and skill levels of the GAA players. After each session and match, the players data is synced and exported onto the platform. Access to the performance data was facilitated through the team management, as they are the only individuals with authorized access to the platform, sessions from November to March were exported and shared as a csv file.

This approach was selected because it offers numerical, objective data on the physical performance of players, allowing accurate research and comparison over time. The results of this analysis are directly in line with the research objective, which is to assess how well performance monitoring tools improve both individual and team performance.

A structured survey questionnaire was implemented to gather qualitative data, with the aim of gaining insights into participants' perceptions and experiences about the use of their devices. Qualitative surveys seek to harness the potential qualitative data offer for nuanced, in-depth and sometimes new understandings of social issues (Braun et al., 2021). The questionnaire included both closed-ended and open-ended questions on a range of subjects, focusing on social dynamics within the community, team morale, and motivation. Participants were provided with information about the project and were also asked for their consent for their answers and data to be used for the purpose of this study. In order to gather personal information about players' beliefs and motives about the devices, a survey was the best option to offer a structured organised method. By offering extensive contextual information, this approach strengthens the quantitative data and helps the research goal of examining the psychological and social effects of these technologies.

A method considered but ultimately decided against was to carry out interviews. While interviews could provide in-depth qualitative data, they were considered impractical due to issues such as scheduling conflicts and physical distances. Given the sample size of the team, conducting individual interviews for each player would have been time-consuming, making it less feasible within the project timeframe.

Survey design

The most effective and convenient way for participants to submit their answers was carefully considered during the survey preparation process. The choice to create a Google Forms survey was due to the platforms easy to use design and accessibility for participants. Understanding that the athletes have hectic schedules, it was critical to prioritise ease of use and simplicity in order to guarantee high response rates and participation. The anywhere-anytime-access and other advantages such as unlimited surveys, and it being 100% free, have made Google Forms a popular product in online survey research (Vasantha et al., 2016). The participant’s email was requested for identification purposes and for ethical approval, however the participants names were not used and were called as Player 1, Player 2 etc.

Careful consideration and planning went into creating the survey's questions in order to provide a thorough understanding of each aspect of the participants' experiences with the devices. The aim was firstly to learn how the participants felt about using performance data, and second, to find out how it might impact their behaviour, motivation, and interactions within their broader social context.

Participants were provided with a range of response possibilities through the use of a five-point Likert scale, which ranged from "No (not at all)" to "Yes (to a great degree)." This enabled an opportunity of nuanced feedback. In addition to assessing the attitudes and views of the participants, this scale offered some flexibility in response, allowing them to indicate how strongly they agreed or disagreed with each statement. All questions were required to be answered to ensure consistency and completeness. In addition, it was made sure that participants understood the goal of the study and voluntarily consented to the use of their performance data by including a clear consent question at the end of the survey. Throughout the creation of the survey, it was essential to respect participants' right to privacy. To achieve this, specific processes were put together to maintain ethical principles and data safety standards.

1) Does the use of performance monitoring devices influence your motivation to participate in GAA activities?
2) Do you find that feedback from performance monitoring devices has a psychological impact on team morale and motivation
3) Has your behaviour in relation to your athletic performance been influenced by performance data?
4) Do you feel pressure to perform because of the way your community sees you in the team?
5) Do you consent to your performance data being used for the purpose of this study?

The survey was sent electronically via Whatsapp given the widespread use of mobile devices and the convenience it gave participants in the group chat, with a simple message containing the survey link shared in the group chat. All responses were gathered within a relatively short timeframe of two weeks.

Data analysis

The data analysis for this study was structured to maximize insights from both quantitative performance metrics and qualitative survey responses. The aim was to integrate these two data streams to explore the relationships between physical performance, psychological effects, and social dynamics within the GAA team environment.

The structured quantitative data and the qualitative data were formatted in CSV files. The quantitative data was organized into specific columns for each metric allowing for systemic analysis. The qualitative data were organized into a series of responses to the survey questions to assess psychological and social impacts.

Preprocessing and Data Cleaning

The preprocessing involved thorough cleaning protocols to guarantee the accuracy and use of the data gathered, the quantitative data was carefully reviewed for abnormalities or errors in device recordings that could indicate malfunctions or mistakes. It was found that the columns Max Heart Rate (Max HR), Average Heart Rate (Avg HR), and Time In Red Zone had zero values for each entry during the data inspection process. These columns were removed from the dataset when it was found that they were not relevant due to a lack of contribution to the analysis. Generic identities such as "Player1", "Player2", "Player3" and so on have been implemented in place for all 20 individual's identity in order to ensure participant privacy and consistency across the datasets. The anonymization process has been used for both the survey responses and the performance data gathered from monitoring devices. This process of converting each participant name to an anonymous matching identification was carried out before combining and comparing the datasets.

Analysis

Quantitative analysis involved computing basic descriptive statistics for each of the performance metrics. The average values for each of these metrics were computed for each player. After the data was combined, Pearson's correlation coefficient was used to find any connections between the players' answers to the survey questions and the averaged performance metrics. The last question, which asked about the players' consent, was left out due to the response not being numerical, the other five questions were included. The metrics chosen to be compared against the survey responses were total distance, high-speed running, impacts, max speed, and sprint distance. The purpose of this analysis was to figure out the strength and direction of connections between psychological perceptions of motivation, team spirit, behavioural effects, and community views and physical performance levels.

For the qualitative analysis the frequency of the survey responses falling into each category was counted. Understanding the frequency of particular opinions or attitudes among the players was made easier by this quantification.

Tools and software

The particular selection of tools and software significantly improved the quality of this research by making the handling of data, analysis, and visualisation easier. The main programme utilised for statistical analysis and data management was Python. Pandas was used for its handling of data capabilities within the system of Python. This package made it easier to clean, process, and aggregate the massive datasets that performance monitoring devices collected. Its features were necessary for converting data types, solving missing data, and combining datasets. The SciPy library was also used to do statistical calculations, specifically for correlational analysis. This ensured that the analysis of relationships between performance metrics and survey responses was both accurate and statistically valid. Using Plotly, a powerful visualisation tool, several types of visualizations were created to visually explore both the performance data and the survey results. Time series line charts highlighted the trends in performance metrics over the season, while bar charts displayed the frequency of various survey responses, offering a visual comparison of perceived impacts versus actual performance metrics. An interactive dashboard was also developed with Dash by Plotly, allowing to explore different aspects of the data more deeply, such as selecting specific survey questions and seeing the distribution of responses.

The overall objectives of this study are closely linked to the chosen data analysis methods. Using Pearson's correlation, this study directly addresses the idea that certain physical performance measures can predict how players feel psychologically and how well they work as a team. In order to respond to the main research questions, an in-depth evaluation of the survey responses was done rather than just summarising data using simple statistics, thereby addressing the key research questions. These methods were chosen over other ones as they fit well with the data, and also helped clearly show the connections looking to be explored.

Ethical considerations

Informed consent was collected from each participant by completing the survey. Participants were given a brief overview of the purpose and goals of the study, along with the implications of their involvement before completing the survey.

In order to fully give their approval, participants in the survey were asked to state in their response to the last question whether or not they would be willing to share their performance data. By choosing to click "yes," they gave their informed consent and allowed their data to be analysed for the study. On the other hand, participants who chose 'no' were respected in their decision, and their data was not included in the analysis.

Along with this, strict ethical guidelines were followed before data collecting started. This required filling out an ethical approval form and getting approval from the research supervisor and the departmental research officer. This was necessary in ensuring adherence to ethical standards and protecting the interests of the participants and their wellbeing.

In terms of data storage, the participants data would be securely stored on a University College Cork supported cloud storage platform, and that the data will be retained for a period of 13 months following the end of the academic year.

Changes and reflections

The original plan for the research was to use just quantitative information from performance monitoring equipment. However, surveys were added in order to better understand how these measurements affect the psychological and social aspects of athletes' experiences. The goal of this methodological modification was to gain qualitative information that wasn't possible to collect from device data alone. The realisation that quantitative data provides only a limited understanding of the thoughts and behaviours of the athletes inspired the addition of the survey. Through the use of surveys, individual experiences and perceptions could be collected, resulting in a more comprehensive and nuanced dataset. This change allowed for a more comprehensive analysis of the correlation between physical performance and psychological well-being, improving the ability to address the research question more fully. Including qualitative data made it clear how crucial it is for sports science researchers to take into consideration a variety of data sources. Using multiple sources of data is important because it allows researchers to understand not just the physical aspects of sports performance but also the human elements, how athletes feel, what motivates them, and how they interact with their team. This can provide deeper insights that can't be gathered from numbers alone.

Limitations

Sample size: One of the primary limitations of this study is the sample size and its composition. The research was conducted with 20 participants from a single GAA team. Although this sample size works well for initial research and correlations, it might not be large enough to generalise the results to all GAA teams. In addition, the team's responses may have been different from those of teams unfamiliar with advanced monitoring technology due to their prior experience with these devices.

Data Collection Biases: Given that the data collection relied on devices already familiar to the team, there may be biases in how players reported their experiences. Players who are used to being monitored might change their responses which is known as the Hawthorne effect, individuals modify an aspect of their behaviour in response to their awareness of being observed(McCarney et al., 2007).

Survey Design: When compared to other qualitative techniques like group discussions or interviews, the use of surveys to gather qualitative data may limit the depth of insights. Participant replies to surveys are limited, especially when they include closed-ended questions, which means that participants' diverse and nuanced feelings and opinions about their experiences with performance monitoring devices could be left undiscovered. This could result in a simple understanding of the psychological effects.

Lack of Longitudinal Depth: Although the study was designed as a longitudinal analysis, the actual span of the data collection may not fully capture long-term trends and changes in player performance and psychological conditions. Studies with a long duration, covering several seasons or even years offer a more deeper understanding of the effects that consistent usage of performance monitoring has on athletes.

Implementation/ Digital Artefact

For the digital artefact, an interactive visualisation dashboard was developed and created aiming to explore the impact of performance monitoring devices on player and team dynamics within GAA. The primary goal of this artefact was to analyse and visualise how these devices influence both individual and collective performance metrics, as well as psychological and social aspects such as motivation, morale, and community perceptions.

Data cleaning process

The performance data was initially shared as a CSV file, however the survey data was collected by Google forms, which was then exported to CSV format.

Any rows or columns that were identified to show no data or missing values were dropped entirely. Then next stop involved converting all data to appropriate formats, ensuring that dates were in datetime format and numerical values are floats or integers.

Development process and evolution

In the initial phase of the development process, Google Colab (Bisong, E., 2019) was used to build basic bar charts using the CSV files and to get an understanding of the data. As the development progressed the switch was made from Google Colab to Visual Studio Code with Dash, for visualising data in different ways and getting the most out of the data (Dabbas, E., 2021). Initially the dashboard consisted of three basic graphs within a single page application.

To improve the dashboards functionality and aesthetic, the decision was made to advance to a multipage layout. The choice to do so was due to the need for more organised data and the opportunity to demonstrate advanced coding skills. This new multipage style allowed for a more detailed analysis on separate pages significantly improving the user interface and interaction.

Throughout the project new graphs were continuously created and added to the Dash application. This led to a more organised and visually appealing presentation of data.

Technologies used

Visual studio code, a powerful code editor, was a very useful tool during the development. Coding was made easier and more productive by its extensive network of extensions and integrated support for Python and Dash. Choosing an interactive data visualisation board was key to this project due to the dynamic nature of performance data. Dash is a Python web application framework that was chosen because it can create interactive and responsive web applications using only Python. This is especially helpful since it makes it possible to visualise complicated real-time data changes in a way that is very beneficial for in-depth exploratory data analysis. Dash was an ideal tool for creating complex interactive visualisations because of its compatibility with Visual Studio Code and its ability to connect with current Python processes easily.

The digital artifact's scalability and adaptability were important for potential future expansions. Scalability is supported by Dash's flexible design, which makes it possible to include new data sources and visualisations without requiring significant reorganisation. The advanced editing capabilities of Visual Studio Code add to this flexibility by making it easier to improve and alter the application's software in response developing datasets.

Functionalities and Features

Data Integration and Management

The artifact integrates data from various sources from the CSV files containing survey results and performance metrics, allowing seamless management. It uses Python's Pandas library to preprocess, clean, and organise data, including resolving missing values, normalising data types, and merging datasets to produce an organised system for analysis.

The software can also process data in real time, allowing for immediate updates and changes as new information becomes available or parameters are adjusted during analysis.

Page-Specific Implementation

A multipage Dash application was developed using Python, Dash, and Plotly for creating the following interactive visualisations.

To begin, a script was created to initialise the Dash application with Bootstrap integration for styling. The use of “suppress_callback_exceptions=True” allows for callbacks to pages that are loaded automatically, which is useful for multi-page setups.

Following this, the script to configure the navigation and the content that is constantly changing for the multi-page Dash app was created. The user interface of this digital artefact is designed to provide an intuitive and efficient way to interact with complex datasets, facilitating an in-depth analysis of psychological impacts and performance enhancements from using monitoring devices. The user interface is straightforward, featuring a simple navigation bar and a clear layout that organizes data visualisation graphs efficiently. This design ensures the ability to access and analyse data with minimal distractions or complications.

The application has a responsive navigation system which allows quick switching between multiple data displays and analysis models.

```python
#Define the overall layout of the app
app.layout = html.Div([
    dcc.Location(id='url', refresh=False),
    html.Div([
        dcc.Link('Page 1 | ', href='/page1'),
        dcc.Link('Page 2 | ', href='/page2'),
        dcc.Link('Page 3', href='/page3'),
    ], className="nav-links"),
    html.Div(id='page-content')
])
```

Figure 4.1

Page 1 | Page 2 | Page 3

Figure 4.2

<u>Page 1</u>

The first page of the artefact is dedicated to visualizing the results of the survey conducted to gather further psychological insights from the players from questions related to how performance monitoring devices influence their motivation and morale. The aim of this chart is to provide a clear understanding of the distribution and trends of player responses.

The survey data is loaded from the CSV file into a Pandas data frame, which is expected to contain columns where each represent a question and rows represent the responses from each of the players.

The key functionality of this page includes the interactive bar charts that display the distribution of the survey responses to the six questions. These six bar charts were created using Plotly Graph Objects. The width and height of the graphs were adjusted to improve readability, the function split_title as shown in Figure 4.3 was also added and used to prevent the survey question from being cut short.

```python
#split long titles into two lines for better graph display
def split_title(title):
    words = title.split()
    if len(words) > 17:
        return ' '.join(words[:17]), ' '.join(words[17:])
    return title, ''
```

Figure 4.3

```python
#Loop through each column in the DataFrame (excluding the first one), and cre
#Excludes the first column as it's 'Player'
for question in survey_df.columns[1:]:
    #Calculate the percentage of each response.
    question_data = survey_df[question].value_counts(normalize=True) * 100
    question_data.sort_index(inplace=True)


    #Create a bar graph for each question
    fig = go.Figure(
        data=[
            go.Bar(
                x=question_data.index.astype(str),
                #Display percentage on the bars
                y=question_data.values,
                text=[f'{v:.1f}%' for v in question_data.values],
                textposition='auto',
                marker=dict(color='skyblue')
            )
        ]
    )
```

Figure 4.4

The function of this code (Figure 4.4) loads the survey data from a CSV file, and then processes it to calculate the percentage distribution of responses for each question. It then uses Plotly to create a bar chart visualizing these distributions. The addition of interactive hover information on each of the bars enhance user understanding of the graph data points.

<u>Page 2</u>

The second page includes a performance dashboard, designed to provide a better understanding of the players performance data. It contains a layout that is defined with textual descriptions, dropdown menus for selecting players, and graphs to display the data.

The performance data is initially loaded from a CSV file into a Pandas DataFrame. This step involves transforming the 'Session Date' into a datetime format, which ensures that time-based data is accurately processed for subsequent time-series visualisations.

Each visualisation on the dashboard is accompanied by descriptions that provide context and explain the data presented. These descriptions serve as a guide to understand the significance of the metrics and what they say about player and team performance.

Utilizing Plotly Express, the dashboard features a dynamic line graph that tracks key performance metrics such as 'Total Distance' and 'High Speed Running'. The x-axis represents 'Session Date', effectively illustrating performance trends over time.

```python
)
def update_player_graph(selected_player):
    filtered_data = football_df[football_df['Player Name'] == selected_player]
    print(filtered_data.head())  #For debugging
    #Create a line graph using Plotly
    fig = px.line(filtered_data, x='Session Date', y=['Total Distance', 'High Speed Running'], title=f'Performance Over Time for {selected_player}')
    fig.update_traces(mode='lines+markers')
    return fig
```

Figure 4.5

The user interface includes a dropdown menu as seen in Figure 4.7, that allows users to select a specific player from the available dataset. Each selection in the menu represents an individual player and their performance data.

```
dcc.Dropdown(
    id='player-dropdown-page1',
    options=[{'label': player, 'value': player} for player in player_metrics['Player Name'].unique()],
    value=player_metrics['Player Name'].unique()[0],
    multi=False,
    searchable=True,
    placeholder="Select a player"
),
```

Figure 4.6

Player1
Player1
Player10
Player11
Player12
Player13

Figure 4.7

When a player is selected from the dropdown, a callback function is executed. This function filters the entire dataset to include only the selected player's data, and then it creates a line graph that shows the player's performance metrics over time. The graph instantly refreshes to update the selected player's data, creating a personalised view suited to the user's choice. The callback function, implemented with Dash's @app.callback decorator (Figure 4.8), monitors for changes in the dropdown value and adds a new figure to the player's performance graph. It uses Plotly Express to display the line graph, making sure that the visualisation is both informative and engaging.

```
# Callback for updating the player performance graph
@app.callback(
    Output('player-performance-graph-page2', 'figure'),
    [Input('player-dropdown-page2', 'value')]
)
```

Figure 4.8

The static graph on the dashboard provides an aggregated view of the team's average performance metrics over time, focusing on 'Total Distance'. This visualisation provides an overall perspective of the team's progress in distance and acts as a benchmark to assess individual performance within the team's overall context. This overview is beneficial for identifying overarching trends and patterns that might not be visible at the individual level.

```
# Creating the team performance graph statically
team_performance_fig = px.line(
    team_metrics,
    x='Session Date',
    y='Total Distance',
    title='Average Team Total Distance Over Time'
```

Figure 4.9

Page 3

The third page of the dashboard was specifically created to dissect and present the correlation between athletes' performance metrics and their psychological responses to performance monitoring devices. This page uses complex data visualisation techniques to display both individual player data and calculated statistical links, allowing a thorough examination of how performance effects and is perceived by players.

This page features an interactive stacked bar plot that aggregates the survey responses across the multiple performance related questions for each player. The visualisation technique highlights the distribution of responses, allowing for a detailed comparison of how different players perceive the impact of the devices on their performance.

```
#Prepare data for the stacked bar plot
traces = [go.Bar(
    x=Survey_df['Player'],
    y=Survey_df[question],
    name=question,
    marker=dict(color=color),
#Skipping first column and last
) for question, color in zip(Survey_df.columns[1:-1], colours)]
```

Figure 4.10

This code snippet (Figure 4.10) uses Plotly to create a stacked bar plot, where each bar represents a different survey question, coloured differently to improve visual separation and analysis. The plot cleverly integrates responses from the group of players, creating an appealing representation of group attitudes.

Correlations between performance metrics and survey responses are calculated using Pearson's correlation coefficient, which quantifies the degree to which these variables linearly relate to each other. This thorough analysis helps identify important correlations that may influence player performance and opinions.

An interactive data table was then created and used to display the calculated correlation coefficients. The use of colour coding in the correlation table is an excellent way to visually represent the strength and direction of correlations.

```
# Calculate correlation coefficients
correlation_coefficients = {}
for metric_name, metric_values in metrics.items():
    for question, responses in survey_responses.items():
        coefficient = round(pearsonr(metric_values, responses)[0], 3)
        if metric_name not in correlation_coefficients:
            correlation_coefficients[metric_name] = {}
        correlation_coefficients[metric_name][question] = coefficient
```

Figure 4.11

```
dash_table.DataTable(
    id='correlation-table',
    columns=columns,
    data=table_data,
    style_cell={'textAlign': 'center', 'width': '200px', 
    style_header={'fontWeight': 'bold'},
    style_table={'margin-bottom': '50px', 'width': '50%'},
    style_data_conditional=style_data_conditional
)
```

Figure 4.12

Conclusion

This interactive visualisation dashboard was created as a tool to explore the complex effects of performance monitoring devices on player psychology, team dynamics, and community perceptions in the GAA. The dashboard combines survey responses with metrics for performance, providing visualisations such as stacked bar charts and line graphs for analysing correlations and trends in the dataset. The calculated correlation coefficients are used as an outline for exploring possible connections between objective performance data and players' subjective experiences.

Analysis

This analysis section aims to provide a comprehensive evaluation of the interactive visualization dashboard developed to explore the impacts of performance monitoring devices on player psychology and team dynamics within GAA.

The design and development of an interactive visualisation dashboard to display the performance data and survey results gave an exciting chance to examine the various impacts of performance monitoring technology on player behaviour, team dynamics, and community attitudes. Insights gathered from the previous literature review and environmental scan will help guide this process, along with the lessons learned throughout the artefact's design and building phases.

This section further aims to analyse the technological functionalities of the dashboard and look at the numerous insights it provides on player performance and psychological aspects. This analysis will delve into several critical areas, assessing the relationship between the quality of combined data and the usefulness of visualisations in presenting clear and useful information.

The scope of this analysis is broad and multifaceted, covering several key areas including technological evaluation, data quality and visualization effectiveness, user interaction, and a detailed examination of the graph results. First, it will look at the dashboard's performance and usability, including data integration and real-time processing functions. Second, it will examine how the type of the data affects the selection of visualisations and the simplicity of findings presented. Third, the analysis will review how the dashboard facilitates user engagement through intuitive navigation and accessibility. Lastly it will analyse specific graphs to discuss trends, patterns, and correlations in the data.

Technological evaluation

Performance and usability

The dashboard's technological structure is supported by strong data integration and immediate processing capabilities, which are needed for dealing with the intricate datasets found in sports analytics. The dashboard was designed to ensure high performance and usability, creating a simple experience when processing large datasets.

The design of the dashboard incorporates a user interface with easy to follow navigation routes that allow for quick access to the various analysis methods. The layout is basic and organised, leaving little opportunity for confusion.

Data Integration and Real-Time Processing

One of the standout features of the dashboard is its ability to smoothly combine several data sources. The dashboard provides an in-depth understanding of the team's performance dynamics by merging data from wearable devices, team statistics, and individual player analytics onto a single platform. Real-time data processing is another major capability of the dashboard as it provides immediate feedback and analysis on the players workload and psychological states.

Data Quality and Visualization Effectiveness

Impact of Data Type on Visualization Selection

The quality and details of the data play an important role for choosing what visualisations to use on the dashboard. The data collected from performance monitoring devices is often very detailed and complicated, influencing what kinds of visualisations are most effective. For example, time-series data from training sessions was best represented through line graphs that clearly demonstrate changes over time, however the statistical data from player surveys was be more effectively displayed using bar charts or pie charts to illustrate distribution and proportions. Choosing the proper visualisation is important since it affects the ability to interpret data accurately. More complicated information could need advanced visualisations such as heat maps or scatter plots, which can reveal deeper insights. On the other hand, excessively complicated visualisations could affect simpler data sets, resulting in data confusion or misinterpretation. As a result, selecting visualisations that would accurately correspond with the performance data and survey replies was crucial in aiding to answer the research's objective.

Effectiveness of Visualizations

The accuracy of the visualisations is determined by their ability to convey the intended insights clearly and efficiently. An effective visualisation allows a quick understanding of key ideas without being overwhelmed by unnecessary complexity. The dashboard aims to achieve a balance between simplicity and helpful depth, guaranteeing that each visualisation is understandable while yet providing lots of insights. Certain graphs did not function as planned due to the structure of the data or the specific requirements of the study. For example, a scatter plot designed to highlight relationships between the two variables could turn out ineffective as the data is overly clustered or if outliers skew the interpretation.

Challenges with Data Quality

Data quality issues like missing numbers or inconsistencies can have a significant effect on the accuracy of visualisations. These mistakes could result in misleading graphs, leading to inaccurate conclusions. To avoid these risks, the dashboard contains data cleaning and processing methods that improves the quality of data before it is visualised. These steps involve dealing with missing data using imputation techniques, filtering out noise with data aggregation techniques and checking data consistency using automated checks.

User interaction

Simple Navigation and Accessibility

The dashboard has an easy-to-follow navigation structure that makes it easier to access the numerous pages. The dashboard has an easy-to-follow navigation structure that makes it easier to access the numerous pages. The layout is designed to allow straightforward manoeuvring between the different data visualisations and analytical tools. This set up allows more focus for interpreting the data rather than figuring out how to navigate the system.

Data Interaction

Interactive features are a highlight of the dashboard, allowing for active user engagement with the data. Tools like clickable legends, hover information, and draggable sliders allow the to engage directly with the visualisations. These interactive features not only make the research more engaging, but they also allow for a deeper examination of the data, leading to a better understanding of key trends and patterns.

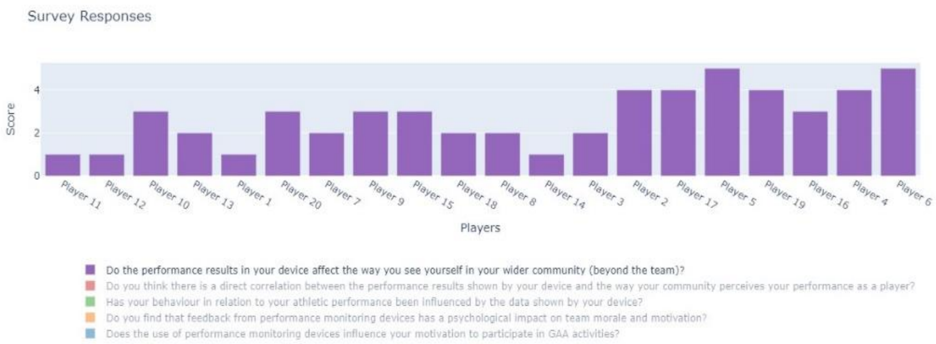

Figure 5.1

Detailed Examination of Graph Results

Bar Charts: Survey Response Distribution

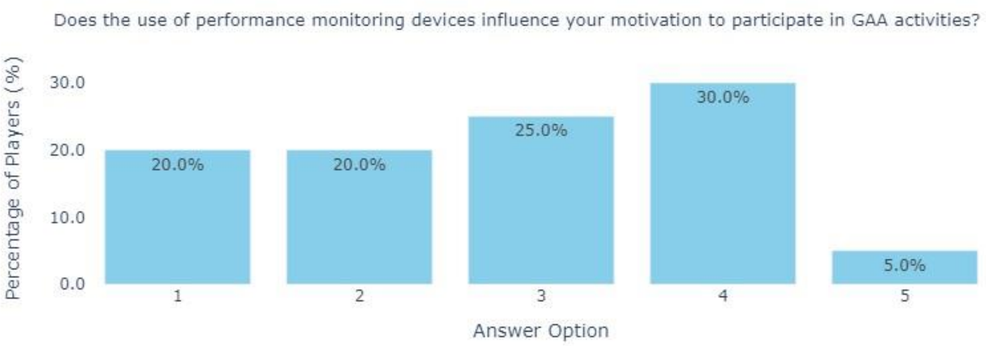

Figure 5.2

The bar chart as seen in Figure 4.1 shows the impact of performance monitoring devices on motivation shows a wide range of responses, with a clear lean towards increased motivation (scores of 3 and 4 account for 55% of replies). This shows that, while the majority find these devices motivating, there is some variation in how players perceive their influence.

This finding corresponds with the study found which suggests that performance monitoring might boost motivation by giving athletes with clear feedback that allows them to track their progress and set specific goals. Performance data can influence an athlete's self-efficacy, which is their belief in their ability to succeed in specific situations. Seeing improvements in performance data can enhance self-efficacy, thereby increasing motivation (Szarabajko et al., 2023). On the other hand, consistently poor performance data might undermine self-efficacy, potentially reducing motivation unless the athlete has strong resilience and support. The frequency of lower scores (1 and 2) confirms consistently poor performance data might undermine self-efficacy, potentially reducing motivation unless the athlete has strong resilience and support.

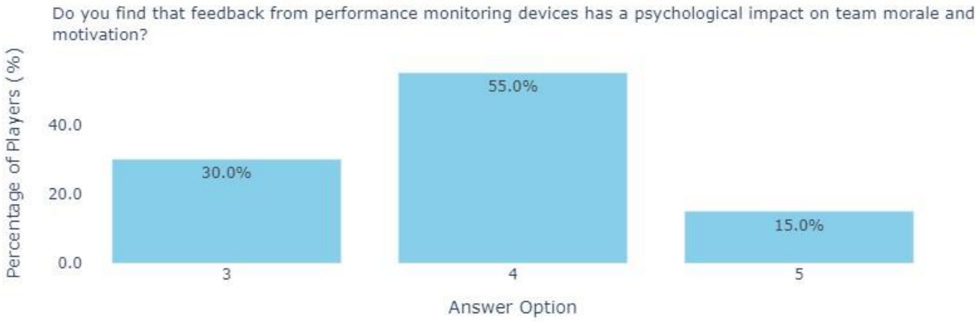

Figure 5.3

The majority (70%) believe performance devices have a high to very high impact on team morale and motivation, indicating that these devices are recognised as being beneficial for improving teamwork. (Figure 4.2)

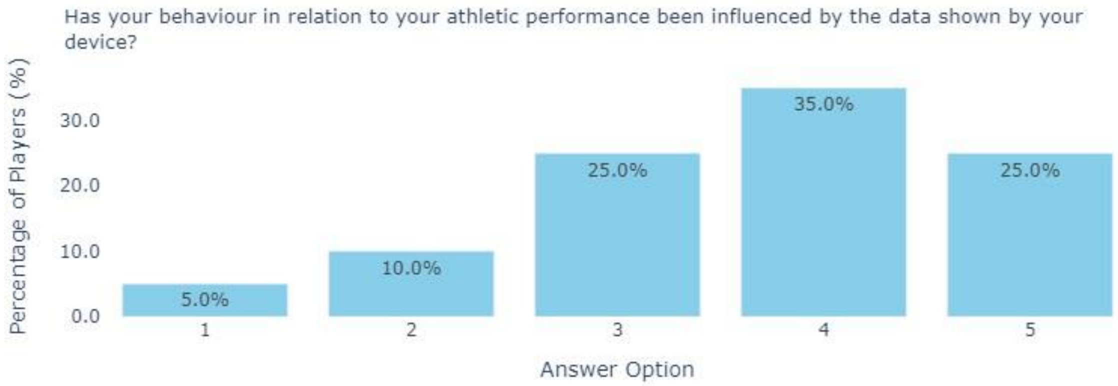

Figure 5.4

Responses in Figure 4.3 strongly agree with the influence of performance data on athletic behaviour (65% rated high to very high influence), implying that the athlete's attitude is greatly impacted based on the data they get from their trainings and matches. The findings support the idea that training data feedback significantly influences behaviour improvement among players. In research carried out by Nosek et al., (2021) players responded positively to receiving specific feedback on metrics like total distance covered, high-speed running, and sprint distances. This type of targeted feedback helped the players understand specific areas of their performance that need improvement, which motivated them to adjust and enhance their behaviour during training and matches.

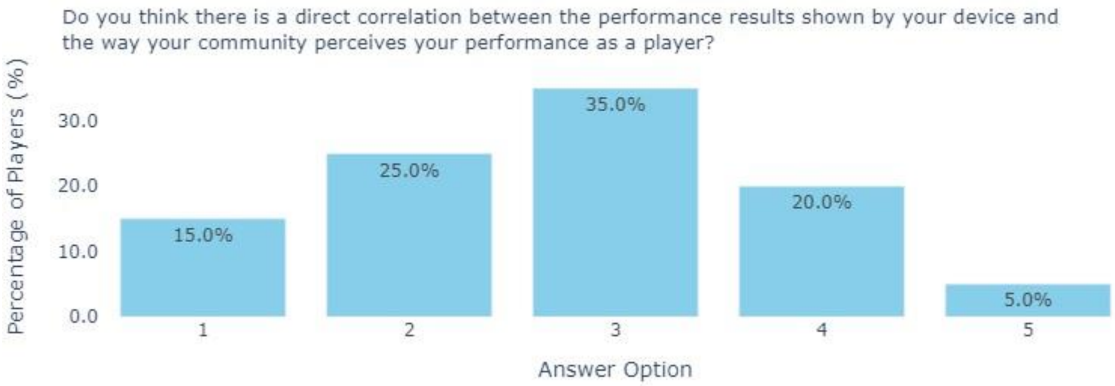

Figure 5.5

The responses indicate a moderate to strong perceived link between device data and community perceptions of performance (Figure 4.4). This indicates a conscious awareness among players about the external validation of their performance metrics.

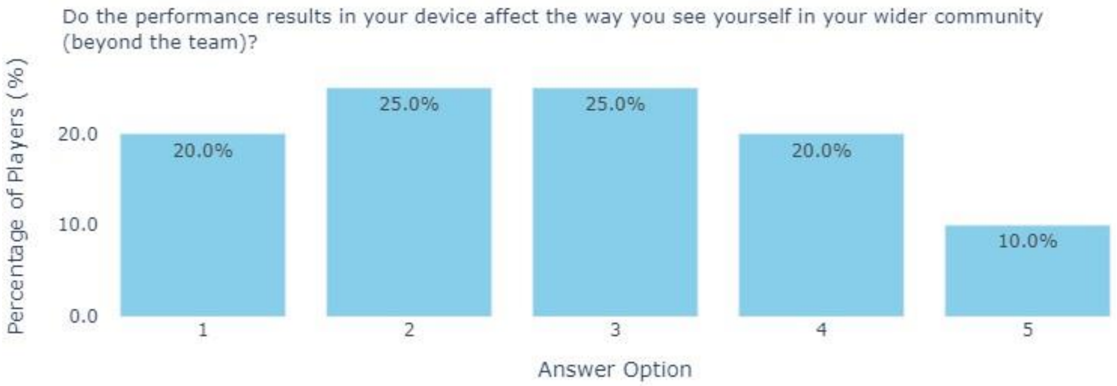

Figure 5.6

The range of answers shows that people have different reactions to how performance data influences their self-perception outside of the team environment. While 50% felt moderate to very high impact, a significant 45% had little to no impact (Figure 4.5). Feeling pressure to perform for others can shift an athlete's focus from internal goals such as personal bests and self-improvement to external outcomes such as winning for the team or pleasing an audience. This shift can sometimes distract from the process needed to achieve performance, focusing too much on outcomes rather than on performance itself (Cowden, R.G., 2017).

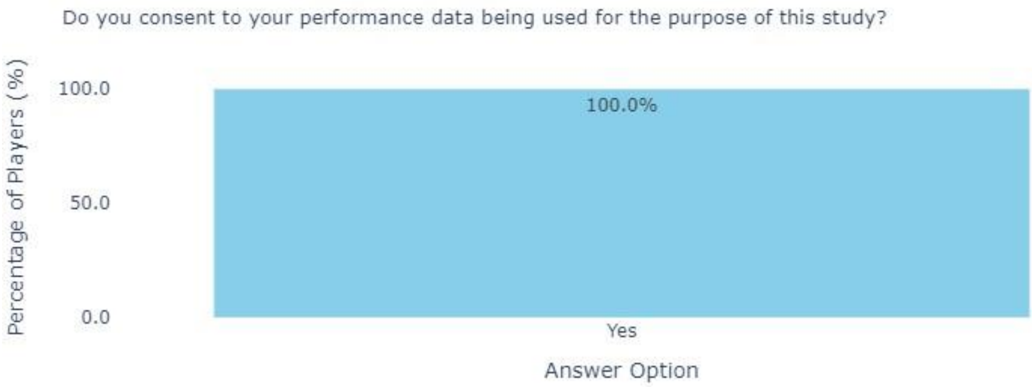

Figure 5.7

Each participant in Figure 4.6 who completed the survey agreed to submit their performance data for the study.

The bar chart survey responses provide a nuanced view of how performance monitoring devices affect many psychological and social aspects of the players' lives. Overall, the empirical data gathered mainly supports the beneficial impacts noted in previous research, but it also emphasises the complexities of individual perception and response.

Line charts: performance overview

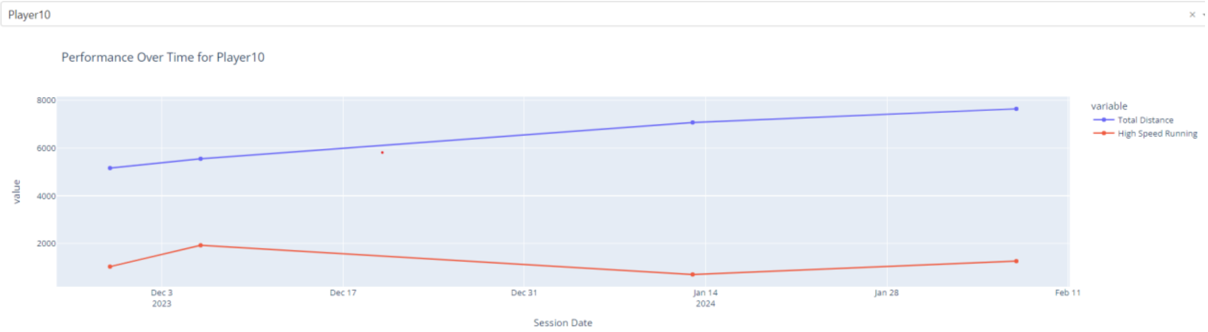

Figure 5.8

By examining the fluctuations in performance metrics like distance covered and high-speed running, patterns or anomalies can be identified in player performance. For example, spikes in high-speed running may suggest games or sessions in which the player was extremely active, which can be correlated with fitness levels, or effectiveness of training. It is a beneficial way to get an overview of the players performance overtime.

Figure 5.9

The team performance graph provides insights into how well the team performs as a unit. The line graph illustrating the average 'Total Distance' covered by the team's performance in Figure 4.8, reveals a progressive increase in distances covered over the observed period.

The use of a line graph to visualise the individual player data and the team's data was a beneficial choice to observe any patterns or progress. This trend suggests a successful adaptation to the training program, reflecting an improvement in the players' overall fitness and endurance.

Stacked bar plot

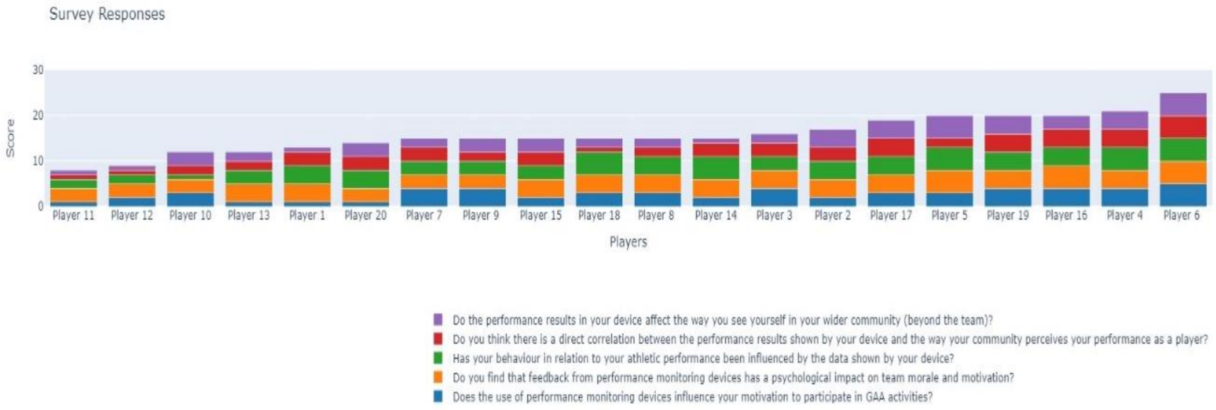

Figure 5.10

The chart aggregates the responses to the numerous survey questions into one visual framework, allowing for an at a glance comparison of the variety of player perceptions across the different aspects of performance monitoring. The chart presents a simple comparison of how perceptions vary among team members by arranging the players along the x-axis based on the level of their responses, from low to high. This order shows patterns and outliers making it easy to identify which of the players are most receptive to the technology. Each bar in the chart represents an individual player and is segmented by their responses to the different questions. Each question has its own unique colour to visually differentiate the type of response attributed to the various aspects of performance monitoring. These different colours simplify the charts information making it easier to analyse providing a quick summary of the data.

Players at the beginning of the graph, such as Player 11, Player 12, and Player 10, may be sceptical of the usefulness or utility of performance monitoring. However, in comparison to the players like Player 6, Player 4 and Player 16, who rate the impact of the devices highly, likely see the benefits in their training and performance. Olmedilla et al., (2019) emphasises the importance of an athlete's psychological disposition in sports performance. The study provides the link between physical, technical, and tactical skills and competitive performance, showing that psychological factors have a considerable impact on how players perceive their own performance.

Correlation Table

To further attempt to answer the research question another way to look at the data combined was to calculate the Pearson correlation coefficient between the survey questions and certain metrics. While it is understood that trying to link objective performance data such as speed and distance with subjective data linked to players responses is an ambitious goal, this correlation table was created as a different approach to visualise the relationship between certain metrics and the players perceptions.

0 to 1 - Positive Correlation   -1 to 0 - Negative Correlation

Performance Metric	Motivation	Team morale	Behaviour	Perceived performance	Community impact
Total Distance	-0.321	-0.418	-0.308	-0.172	-0.235
High Speed Running	-0.077	-0.191	-0.074	-0.274	-0.093
Impacts	0.057	0.136	0.019	0.117	0.03
Max Speed	-0.481	-0.171	-0.206	-0.368	-0.192
Sprint Distance	-0.436	-0.512	-0.39	-0.462	-0.317

Figure 5.11

As a result, Total Distance covered has negative correlations with all aspects measured. As well as this High Speed Running was similar but with weaker correlations. Impacts show weak positive relationships with all parameters, however the coefficients are extremely low. This could indicate that higher impacts during games or trainings might have a marginally positive effect on players, perhaps due to the intensity levels perceived during more physical sessions. Max Speed can be seen to have the strongest negative correlation with motivation and perceived performance. Furthermore, Sprint Distance correlates negatively with all surveyed aspects, particularly strongly with team morale. This statistic could reflect a source of stress suggesting that greater sprint lengths may have a negative influence on players' psychological and social well-being possibly because of the high physical demands.

With the help of these statistics results, it is seen that there is a weak correlation between the data and the players survey responses. While the analysis indicated possible findings, given the weak strength of these correlations and the limitations of the projects dataset, these observations should be considered with caution and confirmed through further and more comprehensive studies. However, while attempting to answer the research question, the project has significantly enhanced the proficiency in the use of digital analytical tools and the application of statistical analysis techniques such as the Pearsons correlation coefficient, has been helpful for identifying the links within the data.

Conclusion

This study conducted an in-depth look into how modern performance monitoring technology influence GAA players' behaviours and performance. The study proved that these technologies not only improve performance metrics but also have a significant impact on psychological and social dynamics within the team. This conclusion reflects the performance data gathered, showing the powerful as well as complex effects of such technologies on player psychology in GAA.

The quantitative data was successfully collected from the Statsport wearable devices, gathering metrics to measure each of the players speed, agility, and endurance. At the same time the qualitative research looked deep into the players psychology and social aspects within the team. The findings suggested a wide range of psychological responses. While many athletes were motivated and morally boosted by the data given by the monitoring tools, a number of those who took part also felt pressured, which they said had a negative impact on their self-perception and sense of belonging within the community.

The development of the digital artefact, an interactive visualisation dashboard, has been critical to the practical implementation of this research. This interactive visualisation dashboard served as a platform to assess the athlete’s performance data individually and as a team but also offered the opportunity to analyse the data. It also neatly displayed the results of the survey, with the combination of both being shown, the dashboard offered insights into the trends and results, which further helped answer the question regarding the relationship between the performance data and the players survey responses.

While a lot of information was gathered from both datasets, the mixed-methods approach provided insights into the relationship between performance data and perceptions, despite the challenges of aligning objective and subjective data. To deal with this, a detailed analytical method was carried out. The study aimed to investigate potential correlations, and to do this, statistical analysis techniques such as Pearsons’s correlation coefficient was used to help identify any correlations between the data. As a result, it is seen that there is a weak correlation between the players performance data and their survey responses, however it is acknowledged that linking measurable data with abstract player attitudes was ambitious, and this becomes even more difficult if the reduced size of the dataset is considered. Nevertheless, insights into the use of digital tools and various ways to display data were gained during this research.

This research has improved the understanding of the impact of performance monitoring technologies on team dynamics and individual performance within GAA sports. However, reflecting on alternative approaches shows potential avenues for further exploration. For instance, an alternative approach could have included more diverse data collection techniques such as interviews with the players. This method could offer more nuanced insights into the players psychological experiences and reactions to the technology, potentially offering a greater understanding into the aspects of team dynamics and social behaviours that surveys alone may not capture.

The study could benefit from a longer duration to track changes over multiple seasons, providing insights into the long-term effects of performance monitoring. Aswell as this, expanding the participant base to include more diverse GAA teams could help generalize findings across different levels and regions.

Bibliography

AK, M.O., 2021. SPOR YÖNETİMİ AÇISINDAN TEKNOLOJİNİN SPORA ENTEGRESİ CYBATHLON ÖRNEĞİ. PEARSON JOURNAL, 6(16), pp.413-427.

Akenhead, R. and Nassis, G.P., 2016. Training load and player monitoring in high-level football: current practice and perceptions. International journal of sports physiology and performance, 11(5), pp.587-593.

Arlotti, J.S., 2022. Benefits of IMU-based wearables in sports medicine...Berg, M.F., Døsvik, H., Skjølsvik, K.Ø., Pedersen, T.S., Aasan, V., Steinert, M. and Eikevåg, S.W., 2023. Wireless sensor system for real-time performance monitoring in sports. Frontiers in Sports and Active Living, 5, p.1305117.

Bădescu, D., Zaharie, N., Stoian, I., Bădescu, M. and Stanciu, C., 2022. A narrative review of the link between sport and technology. Sustainability, 14(23), p.16265.

Bailon, C., Damas, M., Pomares, H., Sanabria, D., Perakakis, P., Goicoechea, C. and Banos, O., 2018, October. Intelligent Monitoring of Affective Factors Underlying Sport Performance by Means of Wearable and Mobile Technology. In Proceedings (Vol. 60, No. 1). MDPI.

Bailon, C., Damas, M., Pomares, H., Sanabria, D., Perakakis, P., Goicoechea, C. and Banos, O., 2018, October. Intelligent Monitoring of Affective Factors Underlying Sport Performance by Means of Wearable and Mobile Technology. In Proceedings (Vol. 60, No. 1). MDPI.

Bisong, E. and Bisong, E., 2019. Google colaboratory. Building machine learning and deep learning models on google cloud platform: a comprehensive guide for beginners, pp.59-64.

Braun, V., Clarke, V., Boulton, E., Davey, L. and McEvoy, C., 2021. The online survey as a qualitative research tool. International journal of social research methodology, 24(6), pp.641-654.

Brown, K.M., Hoye, R. and Nicholson, M., 2014. Generating trust? Sport and community participation. Journal of Sociology, 50(4), pp.437-457.

Camerino, O., Castañer, M. and Anguera, T., 2012. Mixed Methods Research in the Movement Sciences: Case studies in sport, physical education and dance. Routledge.

Camomilla, V., Bergamini, E., Fantozzi, S. and Vannozzi, G., 2018. Trends supporting the in-field use of wearable inertial sensors for sport performance evaluation: A systematic review. Sensors, 18(3), p.873.

Cowden, R.G., 2017. On the mental toughness of self-aware athletes: Evidence from competitive tennis players. South African Journal of Science, 113(1-2), pp.1-6.

Crang, Z.L., Duthie, G., Cole, M.H., Weakley, J., Hewitt, A. and Johnston, R.D., 2022. The inter-device reliability of global navigation satellite systems during team sport movement across multiple days. Journal of Science and Medicine in Sport, 25(4), pp.340-344.

Cullen, B.D., McCarren, A.L. and Malone, S., 2021. Ecological validity of self-reported wellness measures to assess pre-training and pre-competition preparedness within elite Gaelic football. Sport Sciences for Health, 17(1), pp.163-172.

Dabbas, E., 2021. Interactive Dashboards and Data Apps with Plotly and Dash: Harness the power of a fully fledged frontend web framework in Python–no JavaScript required. Packt Publishing Ltd.

Duggan, J.D., Moody, J.A., Byrne, P.J., Cooper, S.M. and Ryan, L., 2021. Training load monitoring considerations for female Gaelic team sports: from theory to practice. Sports, 9(6), p.84.

Eime, R.M., Payne, W.R. and Harvey, J.T., 2008. Making sporting clubs healthy and welcoming environments: a strategy to increase participation. Journal of Science and Medicine in Sport, 11(2), pp.146-154.

Flynn, L. (2023) 20 advances in technology that will help athletic performance, Money Inc. Available at: https://moneyinc.com/advances-in-technology-that-will-help-athletic-performance/

Gallagher, L., 2019. The relationship between mental toughness and mental health in GAA players.

Halson, S.L., 2014. Monitoring training load to understand fatigue in athletes. Sports medicine, 44(Suppl 2), pp.139-147.

Hanin, Y.L., 2003, January. Performance related emotional states in sport: A qualitative analysis. In Forum qualitative sozialforschung/Forum: qualitative social research (Vol. 4, No. 1).

Iervolino, R., Bonavolontà, F. and Cavallari, A., 2017, September. A wearable device for sport performance analysis and monitoring. In 2017 IEEE international workshop on measurement and networking (M&N) (pp. 1-6). IEEE.

Izzo, R., Seccia, R., Giovannelli, M., Cejudo, A. and Varde'i, H.C., 2022. Symmetry and performance index evaluation in a youth football group using the latest generation IMU. Journal of Physical Education and Sport, 22(3), pp.782-789.

Keane, J., 2001. The Role of the GAA in Creating, Maintaining and Reinforcing Senses of Place and Identity (Doctoral dissertation, National University of Ireland Maynooth).

Kolt, G.S., 2015. The psychological side of sport. Journal of science and medicine in sport, 18(3), p.237.

Kos, A., Wei, Y., Tomažič, S. and Umek, A., 2018. The role of science and technology in sport. Procedia Computer Science, 129, pp.489-495.

Lavallee, D., Sheridan, D., Coffee, P. and Daly, P., 2019. A social support intervention to reduce intentions to drop-out from youth sport: The GAA super games centre. Psychosocial Intervention, 28(1), pp.11-17.

Lee, C., 2019. Life Satisfaction, Depression & Perceived Stress in GAA inter-county and club players.

Li, R.T., Kling, S.R., Salata, M.J., Cupp, S.A., Sheehan, J. and Voos, J.E., 2016. Wearable performance devices in sports medicine. Sports health, 8(1), pp.74-78.

Mammen, G. and Faulkner, G., 2013. Physical activity and the prevention of depression: a systematic review of prospective studies. American journal of preventive medicine, 45(5), pp.649-657.

McCarney, R., Warner, J., Iliffe, S., Van Haselen, R., Griffin, M. and Fisher, P., 2007. The Hawthorne Effect: a randomised, controlled trial. BMC medical research methodology, 7, pp.1-8.

Memmert, D. and Rein, R., 2018. Match analysis, big data and tactics: current trends in elite soccer. German Journal of Sports Medicine/Deutsche Zeitschrift fur Sportmedizin, 69(3).

Neville, J., Wixted, A., Rowlands, D. and James, D., 2010, December. Accelerometers: An underutilized resource in sports monitoring. In 2010 Sixth international conference on intelligent sensors, sensor networks and information processing (pp. 287-290). IEEE.

Nosek, P., Brownlee, T.E., Drust, B. and Andrew, M., 2021. Feedback of GPS training data within professional English soccer: a comparison of decision making and perceptions between coaches, players and performance staff. Science and medicine in football, 5(1), pp.35-47.

Olmedilla, A., Ruiz-Barquín, R., Ponseti, F.J., Robles-Palazón, F.J. and García-Mas, A., 2019. Competitive psychological disposition and perception of performance in young female soccer players. Frontiers in psychology, 10, p.447878.

Omoregie, P.O., 2016, August. The impact of technology on sport performance. In Proceedings of INCEDI 2016 Conference 29th31st August.

Palinkas, L.A., Horwitz, S.M., Green, C.A., Wisdom, J.P., Duan, N. and Hoagwood, K., 2015. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. Administration and policy in mental health and mental health services research, 42, pp.533-544.

Plews, D.J., Laursen, P.B., Stanley, J., Kilding, A.E. and Buchheit, M., 2013. Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring. Sports medicine, 43, pp.773-781.

Rabbani, A., Kargarfard, M. and Twist, C., 2020. Fitness monitoring in elite soccer players: group vs. individual analyses. The Journal of Strength & Conditioning Research, 34(11), pp.3250-3257.

Rana, M. and Mittal, V., 2020. Wearable sensors for real-time kinematics analysis in sports: A review. IEEE Sensors Journal, 21(2), pp.1187-1207.

Ravindranathan, S., Ardakani, H.D., Pimental, A., Lee, J., Care, N. and Clark, J.F., 2017. Performance monitoring of soccer players using physiological signals and predictive analytics. NSF I/UCRC for Intelligent Maintenance Systems (IMS), pp.1-11.

Rein, R. and Memmert, D., 2016. Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. SpringerPlus, 5, pp.1-13.

Reyes-Bossio, M., Corcuera-Bustamante, S., Veliz-Salinas, G., Villas Boas Junior, M., Delgado-Campusano, M., Brocca-Alvarado, P., Caycho-Rodríguez, T., Casas-Apayco, L., Tutte-Vallarino, V., Carbajal-León, C. and Brandão, R., 2022. Effects of psychological interventions on high sports performance: A systematic review. Frontiers in Psychology, 13, p.1068376.

Ribeiro, J.N., Monteiro, D., Sampaio, J., Couceiro, M. and Travassos, B., 2023. How weekly monitoring variables influence players' and teams' match performance in elite futsal players. Biology of Sport, 40(1), pp.77-83.

Ride, J., Ringuet, C., Rowlands, D., Lee, J. and James, D., 2013. A sports technology needs assessment for performance monitoring in swimming. Procedia Engineering, 60, pp.442-447.

Ryan, J., Edney, S. and Maher, C., 2019. Anxious or empowered? A cross-sectional study exploring how wearable activity trackers make their owners feel. BMC psychology, 7, pp.1-8.

Samełko, A., Guszkowska, M. and Gala-Kwiatkowska, A., 2018. Affective states influence sport performance in swimming. Polish Journal of Sport and Tourism, 25(4), pp.21-26.

Seçkin, A.Ç., Ateş, B. and Seçkin, M., 2023. Review on Wearable Technology in sports: Concepts, Challenges and opportunities. Applied Sciences, 13(18), p.10399.

Szarabajko, A., Gore, J.S., Foster, Z., Katzman, J. and Pope, C., 2023. Winning for our sake: Relational motivation in athletic performance. Journal of Sport Behavior, 46(4), pp.40-59.

Vasantha Raju, N.N.S.H. and Harinarayana, N.S., 2016, January. Online survey tools: A case study of Google Forms. In National conference on scientific, computational & information research trends in engineering, GSSS-IETW, Mysore.

Waegli, A., Guerrier, S. and Skaloud, J., 2008, May. Redundant MEMS-IMU integrated with GPS for performance assessment in sports. In 2008 IEEE/ION Position, Location and Navigation Symposium (pp. 1260-1268). IEEE.

Woods, S., Dunne, S., McArdle, S. and Gallagher, P., 2020. Committed to Burnout: An investigation into the relationship between sport commitment and athlete burnout in Gaelic games players. International Journal of Sport Psychology, 51(3), pp.247-270.