



Understanding the Drivers of Cancellations and No-Shows in Sports Field Reservations: A Practical Case Study with FIELD

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Dissertation submitted in partial fulfillment of requirements for the
MSc in Business Analytics, at the Universidade Católica
Portuguesa, January 2026.

Abstract

Title: Understanding the Drivers of Cancellations and No-Shows in Sports Field Reservations: A Practical Case Study with FIELD

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This thesis addresses the understanding of cancellations and no-show drivers. Despite possessing records from 2019 to 2025, the company relied on an operational database that required manual analysis, leading to a more time-consuming identification of the reasons for cancellation. A Decision Support System was developed, with the methodological analysis progressing from a conceptual model to a star schema, ensuring the correct integration of data, resulting in the production of interactive dashboards in Power BI. Three distinct categories of cancellation drivers were analyzed, focusing on the characteristics of the matches, the attributes of the fields, and temporal and geographical aspects. The analysis identified possible drivers, such as longer lead times and “weekly” recurring slots. Football 5 and prime-time windows also show significant instability in the completion of scheduled matches, as do matches played on wooden pitches or fields with few reviews. Seasonality and location also play a measurable role as possible drivers. The solution validation involved tests conducted by FIELD stakeholders using the Task-Based Usability Test and supplemented with the System Usability Scale, demonstrating with strong evidence that the DSS has high usability, reduces Time-to-Insight, and is geared towards the specific context of the company. These results show that cancellations are not random occurrences but result from specific drivers and that the tool optimizes the TTI, compared to what was in effect, accelerating the company’s decision-making process.

Keywords: business intelligence, decision support system, data visualization, cancellation behavior, dimensional modeling, usability

Resumo

Título: Compreensão dos Determinantes de Cancelamentos e No-Shows em Reservas de Campos Desportivos: Um Caso de Estudo Prático com a FIELD

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Esta tese aborda a compreensão dos determinantes de cancelamentos e no-shows. Apesar de possuir registos de 2019 a 2025, a empresa dependia de uma base de dados operacional que exigia uma análise manual, levando a uma identificação mais demorada das razões de cancelamento. Foi desenvolvido um Sistema de Apoio à Decisão, com a análise metodológica a progredir de um modelo conceptual para um star schema, garantindo a correta integração dos dados, resultando na produção de dashboards interativos em Power BI. Foram analisadas três categorias distintas de determinantes de cancelamento, focando-se nas características dos jogos, nos atributos dos campos e nos aspetos temporais e geográficos. A análise identificou possíveis determinantes, tais como lead times mais longos e as vagas recorrentes “semanais”. O Futebol de 5 e os horários nobres também mostram uma instabilidade significativa na realização dos jogos agendados, tal como os jogos disputados em pisos de madeira ou em campos com poucas avaliações. A sazonalidade e a localização também desempenham um papel mensurável como possíveis determinantes. A validação da solução envolveu testes conduzidos pelos stakeholders da FIELD utilizando o Task-Based Usability Test e complementados com a System Usability Scale, demonstrando com fortes evidências que o DSS possui elevada usabilidade, reduz o Time-to-Insight e está orientado para o contexto específico da empresa. Estes resultados mostram que os cancelamentos não são ocorrências aleatórias, mas resultam de determinantes específicos, e que a ferramenta otimiza o TTI, comparativamente ao que estava em vigor, acelerando o processo de tomada de decisão da empresa.

Palavras-chave: inteligência de negócios, sistema de apoio à decisão, visualização de dados, comportamento de cancelamento, modelação dimensional, usabilidade

Acknowledgments

Now that the time has come to submit this dissertation, I can't help but reflect on everything it means. More than just a thesis, it's the final result of a chapter that's closing, and what a chapter it has been. I feel proud by everything I've achieved during my five years of academic life, both inside and outside the university. I take with me fantastic experiences that will stay with me for life, but even more than those experiences, I'm extremely happy to take with me all the people with whom I shared those experiences and who supported me throughout this time.

I begin by thanking my supervisors, Professor José Coelho and Professor Diogo Lima, for all their support and patience throughout these months and for constantly wanting me to deliver the best work. A huge thank you to the friends I have kept since my bachelor's — Maria, Cabrita, Lourenço, and António — for all the constant motivation they give me, and to the friends Junior Enterprises Portugal gave me — Francisco, Ricardo, and Débora — for all the laughter and for helping me overcome every challenge. I am also grateful to all my friends from Évora living in Lisbon, who always made me feel at home, with a very special mention to Guilherme and Pedro, for their companionship every day.

Finally, my most heartfelt thanks go to my family for all the love, support, and motivation. To my parents, who worked so hard so I could have all the opportunities I have and who support me in everything I do. To my brother, who despite being stubborn, always wants to know what I'm doing. To my grandparents, wherever they are, I hope they are proud of me. To my grandmothers, who raised me from childhood and want to know if the course will pay well. And to my beloved Madalena, my daily support and who makes me enjoy every moment of life. To everyone, thank you, because without you, this wouldn't be possible.

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List of Abbreviations

Abbreviation	Definition
DSS	Decision Support System
BI	Business Intelligence
DB	Database
JSON	JavaScript Object Notation
ID	Identifier
PK	Primary Key
VS Code	Visual Studio Code
iOS	iPhone Operating System
CSV	Comma Separated Values
KPI	Key Performance Indicator
SUS	System Usability Scale
UX	User Experience
UI	User Interface
TTI	Time-to-Insight
SSBI	Self-Service Business Intelligence

1 Introduction

There are 7782 sports facilities registered in Portugal by the National System of Sports Information. These facilities are owned by municipalities, clubs, or associations that most of the time lack the time or resources to develop a platform that allows other people to rent these spaces when they are not being used, in order to generate additional income. It was to answer this problem that FIELD was created, a company focused on renting sports fields, facilitating the life of the owners, who just need to register their space on the app or website and FIELD does the rest, allowing customers to rent a field from anywhere, anytime.

As of today, FIELD rents football, tennis, padel and squash fields in twelve different districts in Portugal and also in the island of Madeira, with the objective of expanding to other districts. However, they have been struggling with a specific problem: cancellations and no-shows. When a client books a field for a certain hour, it will no longer be available for other clients, and if the client cancels with little notice, it can happen that nobody books it afterwards, leading to a loss of revenue and operational inefficiencies for the owner but mainly for FIELD.

This type of behavior is a documented challenge across various service industries, where their negative impact on operational efficiency is recognized. Extensive literature, encompassing sectors from hospitality to general appointment scheduling, indicates that cancellations and no-shows compromise revenue management, resulting in lost bookings, indirect costs, and capacity underutilization (António, de Almeida, & Nunes, 2019; Chen, 2016; Kheirkhah et al., 2016b). Despite this research, the specific domain of sports field management remains largely unexplored. This gap is not merely sectoral but also methodological. While a significant portion of existing studies focuses on developing predictive models to forecast cancellation probabilities, there is a scarcity of research dedicated to descriptive Decision Support Systems (DSS) designed to reveal the underlying causes of such behaviors. Therefore, beyond its immediate practical value for the company, this study holds academic relevance by extending the application of DSS to a novel service environment and by shifting the focus from pure prediction to the interpretability of cancellation drivers.

Turning the attention back to the specific reality of the company and seeking to quantify the extent of this issue within its operations, an examination of the booking records was conducted. Analyzing

the data spanning from 2019 to 2025, it was possible to identify a cancellation rate of 26.52%. From an operational perspective, this figure is considered critical by the stakeholders, as it indicates that more than a quarter of the initially scheduled matches end up being cancelled. The cancellation of these matches led to a total of approximately 442000€ in refunds, corresponding to the sum of the total price of all matches cancelled during this time. It is important to clarify that while this amount represents the total gross value of the bookings, since FIELD would only retain a specific percentage, it clearly demonstrates the substantial magnitude of financial business value that is being lost. It is also possible to assume the loss of revenue resulting from the opportunity cost of not maximizing the potential of the fields.

Given the issues mentioned, it was imperative to build a solution that allows to understand the drivers behind these cancellations. Consequently, this study is grounded in a primary research question: “What are the main drivers of cancellations and no-shows in sports field reservations?”. To provide a comprehensive answer, this central inquiry is decomposed into three specific dimensions, with the rationale behind the selection of them having two reasons. Firstly, they cover main fundamental pillars of a reservation, encompassing characteristics of the activity (Matches), attributes of the infrastructures (Fields), and the temporal and location context (Time/Location). Secondly, this segmentation aligns with the granular data actually captured and stored by FIELD, ensuring the analysis is both theoretically relevant and feasible. Therefore, the study addresses the following sub-questions:

- SQ1: How do specific match characteristics influence the cancellation rate?
- SQ2: To what extent do field attributes impact the reliability of a reservation?
- SQ3: How do temporal and geographical factors affect the likelihood of a match being cancelled?

Variables such as booking channel, lead time, group size, client origin, client type, scheduling around events or holidays, and online reputation can all significantly affect the likelihood of a reservation being cancelled (Falk & Vieru, 2018; António et al., 2019). With the same idea, Amberger and Schreyer (2021) highlight that longer lead times, lower perceived costs of attendance, and the availability of alternatives tend to increase no-show probability across multiple sectors. Applying

this to sports facilities, it is possible to perceive that there are certain factors that affect the outcome of a reservation, and that cancellations don't happen randomly, they are influenced by certain drivers.

To mitigate the problem, FIELD has implemented a strategy to minimize cancellations, which is divided into 3 distinct cases. If the client cancels a field reservation more than 48 hours in advance, they will receive a full refund. If they cancel between 48 and 24 hours in advance, they will only receive half the amount, and if they cancel in the last 24 hours before the reservation or do not show up, they will not be entitled to any type of refund. Such strategies represent potential drivers of cancellation, directly influencing customer behavior and service utilization. Research by Chen (2016) demonstrates that the structure of refund policies (whether full, partial, or non-refundable) significantly affects the risk of late cancellations and the accuracy of utilization forecasts. Specifically, the implementation of tiered policies, in which the refund amount decreases as the booking date approaches, helps to balance the incentive for customers to book early with the deterrence of last-minute cancellations (Chen, 2016; Chen & Vargas, 2011). The findings are, to some extent, consistent with the literature, as we can see in the following graph, with approximately 60% of games being canceled more than 48 hours in advance. However, we can observe that there is a greater number of cancellations occurring in the last 24 hours before scheduling than in relation to cancellations between 24 and 48 hours before.

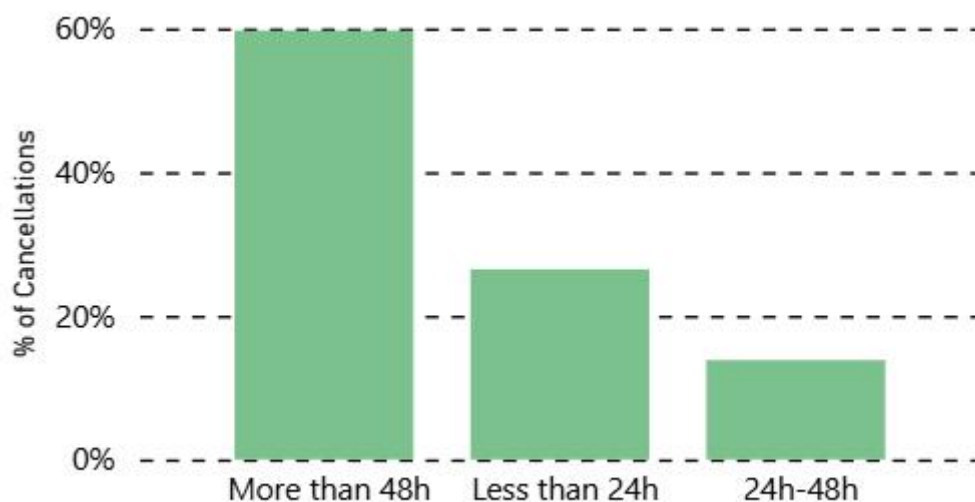


Figure 1: Cancellation Window

Addressing the functional requirement requested by the company, the empirical analysis conducted in this thesis focuses on the development of a Decision Support System. Directed to the operations team, this system serves not only as a technical output but as a methodological contribution, designed to visualize and understand the drivers of cancellations and no-shows. The development follows the methodology used by Schelling et al. (2021), emphasizing modular and user-oriented architectures, and adopts the framework outlined by Ward, Windt, and Kempton (2019), centered on transforming data into actionable knowledge for organizational decision-making. Prior to this study, FIELD possessed a vast amount of raw data but lacked a centralized analytical tool to interpret it. The DSS constructed in this thesis is designed to significantly enhance the speed and intuitiveness of data interpretation. By offering the capability to diagnose the underlying drivers of cancellations in real-time, it supports decision-making grounded in organized and easily accessible data. To do this, the dashboard was designed as a two-layer modular system using data from 2019 to 2025. The first layer concerns data acquisition, processing and integration, aggregating historical booking and cancellation records, companies and user information, match characteristics, fields attributes, and refunds records from the FIELD iOS and Android apps, as well as their website. The objective is to ensure that operational data, previously unstructured and fragmented, is cleaned and transformed into ready-to-use analytical datasets, as detailed in Section 3. The second layer consists of the development of interactive visualizations for decision support, as presented in Section 4. Following the Business Intelligence principles described by Ward, Windt, and Kempton (2019), this layer ensures that the information is presented in an intuitive manner. Regarding this, the central contribution of this thesis extends beyond the mere identification of cancellation drivers, as it demonstrates how data visualization accelerates interpretation and optimizes operational decision-making, focusing on designing a robust solution for FIELD. Section 5 presents the usability validation tests conducted with FIELD stakeholders. These tests combined practical validation with established usability academic protocols to ensure that the dashboard is effective, efficient, and user-friendly. Finally, Section 6 presents the conclusions and limitations, while Section 7 contains the bibliography.

2 Literature Review

2.1 Search Methodology and Scope

To provide a theoretical foundation for this study, a narrative literature review was conducted focusing on the intersection of service operations management and information systems. The review targeted reviewed articles, conference proceedings, and systematic reviews utilizing two primary clusters of keywords. The first cluster focused on the problem domain: “cancellation behavior,” “no-shows”, “revenue management,” and “service reliability.” The second cluster focused on the solution domain: “Business Intelligence,” “Decision Support Systems (DSS),” “dashboard design,” and “sports facility management.” The selected literature was analyzed not merely to catalog existing studies, but to identify methodological divergences and the specific gap regarding the application of diagnostic DSS in recreational sports contexts.

2.2 Cancellation and No-Show Behavior in Reservation-Based Services

The management of capacity in service industries is fundamentally constrained by the perishable nature of the inventory. According to modern service frameworks established by Wirtz and Lovelock (2021), a service unit (such as a sports field) that remains unoccupied for a specific time slot represents a permanent loss of revenue. Within this context, cancellations and no-shows are widely recognized as the primary source of demand uncertainty. The literature identifies a complex set of variables influencing the likelihood of a customer failing to honor a reservation. Systematic reviews by Kheirkhah et al. (2016a) and Amberger and Schreyer (2021) synthesize evidence across sectors, identifying generic factors such as client demographics, timing, and service type. However, this thesis differentiates itself from these reviews by addressing a critical limitation in their scope: while they identify high-level drivers, they fail to account for the granular physical and contextual attributes specific to the activity. Specifically, existing reviews do not explore how distinct Match Characteristics, Field Attributes, and Location interact to influence cancellations.

- **Temporal Factors**

The ‘lead time’ (interval between booking and consumption) is frequently identified as a critical predictor. In this context, Illhet and Klein (2011) demonstrate a positive correlation within the airline and hospitality sectors between extended lead times and cancellation probability, attributing this to the increasing uncertainty of personal schedules over longer horizons.

- **Customer Characteristics**

Research in the healthcare sector, often used as a proxy for appointment-based services, highlights that sociodemographic factors and past behavior (history of no-shows) are strong predictors of future reliability (Dantas et al., 2018).

- **Service Type and Friction**

In the hospitality industry, António, de Almeida, and Nunes (2019) and Falk and Vieru (2018) expanded on this by modeling customer behavior patterns. They argue that the “commitment” to the service varies significantly depending on the booking channel and the perceived value of the reservation.

However, a divergence exists in the literature regarding the predictability of these behaviors. While Falk and Vieru (2018) suggest that modeling customer behavior can capture clear patterns, other authors, such as Gupta and Denton (2008), argue that external, stochastic factors render a portion of cancellations inherently unpredictable, necessitating robust mitigation strategies rather than pure prediction.

2.3 The Role of Cancellation Policies and Customer Decision-Making

Beyond natural drivers, the literature emphasizes that cancellations are also a function of the rules imposed by the service provider. Chen (2016) provides a comparative analysis across hotels, airlines, and restaurants, demonstrating that cancellation policies serve as a “fencing” mechanism. Stricter policies (e.g., non-refundable deposits) reduce the cancellation rate but may also dampen initial demand by increasing the perceived risk for the customer.

- **Consumer Psychology and Decision Making**

The decision to book or cancel is not purely economic, it is also psychological. Chen and Vargas (2011) and Nageswaran, Cho, and Scheller-Wolf (2019) explore the “switching costs” associated with cancellations. They suggest that when customers face low penalties (or flexible omnichannel options), they are more likely to engage in “strategic booking”, meaning holding multiple reservations and cancelling the suboptimal ones at the last minute. Conversely, Sierag et al. (2015) highlight the revenue management trade-off: while lenient policies increase the volume of bookings (conversion), they significantly increase the volatility of the schedule. This body of work suggests that understanding cancellations requires not just analyzing the customer, but also analyzing the incentives created by the company’s policies.

2.4 Business Intelligence and Decision Support Systems

The second theoretical axis of this thesis concerns the tools used to manage these operational challenges. In the era of Big Data, the challenge has shifted from data scarcity to data interpretation. Business Intelligence (BI) and Decision Support Systems (DSS) have emerged as the standard framework for bridging this gap.

- **Critical Success Factors for Decision Support Systems**

The implementation of a DSS is not merely a technical task but an organizational one. Yeoh and Koronios (2010) identified that for a BI system to be effective, it must align strictly with the organization’s decision processes and possess high data quality. Furthermore, the modern approach to DSS has moved away from static reporting. Olszak (2016) and Rizk and Fathey (2022) argue that “interactive visualization” is crucial for user adoption. The system must allow the user to “drill down” into the data to diagnose problems, rather than just viewing surface-level metrics.

- **Layered Frameworks**

Methodologically, Ward, Windt, and Kempton (2019) and Schelling et al. (2021) advocate for “layered, modular dashboards.” This approach separates the data processing layer from the visualization

layer, ensuring that the system is scalable and user-centric. This modularity is particularly important in environments where the end-users are operational managers, not data scientists, requiring the tool to be intuitive and focused on actionable insights (Fuchs, Höpken, & Lexhagen, 2014).

2.5 DSS Applications in Sports and The Research Gaps

While the aforementioned literature is extensive, its application to the specific domain of recreational sports field management reveals significant gaps.

- **The Specificity of the Sports Context**

The sports domain presents unique challenges that distinguish it from hotels or healthcare. Unlike a hotel room (occupied by individuals/couples) or a doctor's appointment (individual), a sports match reservation requires the coordination of a group (e.g., 10 players for a football match). Furthermore, outdoor sports fields are heavily dependent on external uncontrollable factors, specifically weather.

- **Identification of the Research Gaps**

Despite these nuances, the intersection of cancellation analysis and DSS in sports remains under-explored. A critical analysis of the current state of the art reveals three distinct gaps that this thesis aims to address.

Sectoral Gap: the vast majority of cancellation studies focus on hospitality, aviation, and healthcare. There is a scarcity of research dedicated to high-turnover recreational services like sports field rentals.

Methodological Gap (Prediction vs. Diagnosis): most existing studies prioritize complex statistical models to predict cancellation probabilities (Predictive Analytics). However, there is a lack of research on Descriptive and Diagnostic DSS tools that empower managers to understand the root causes of these behaviors.

Drivers of Cancellation Gap: as noted before, existing literature focuses on generic drivers (price, lead time). This study fills a gap by introducing granular determinants specifically: Match Characteristics, Field Attributes, and Location Context, variables which have been largely overlooked in previous systematic reviews.

Ultimately, this thesis bridges the gap between two streams of literature, behavioral research on cancellations and Business Intelligence frameworks. This gap is not defined only by a scarcity of studies, but by the specific absence of visual tools rigorously evaluated with real decision-makers in an operational context. It contributes to the literature by demonstrating how data visualization can be effectively applied to diagnose complex behavioral problems in real-world service environments.

3 Data and Descriptive Statistics

3.1 Data Import and Pre-processing

Following the methodology of Schelling et al. (2021), data acquisition and pre-processing were performed with a focus on integrity and integration. The data was stored in FIELD operational database in Firebase and made available by the company in JSON format. Being a No-SQL database, it is organized by collections, with each entry in these collections being represented by a document ID that then referenced the remaining attributes of that entry. Based on this information and by analyzing how the database was structured, it was possible to understand how to design a relational and analytical database from there: the collections would be considered the entities, with the document ID's being the primary keys for each entry, which would then have their attributes. It was also taken into account that, being a No-SQL database, each document ID could have different attributes within the same collection and that it would be necessary to consider all the attributes that appeared.

The raw dataset initially comprised 37 distinct collections structured in JSON format. A preliminary screening was conducted to evaluate the relevance of each collection against the research objectives defined in Chapter 1. Consequently, six primary collections and one sub-collection were retained: matches, fields, events cancellation, refunds, companies, users, and events (a sub-collection linking fields and matches). These specific collections were selected as they encompass the essential dimensions required to answer the Study Questions (SQs), ensuring high analytical relevance. Specifically, the data regarding fields and companies allow for the examination of infrastructure characteristics and location context, the matches and users collections provide the necessary granularity to identify behavioral patterns and booking details, and finally, the refunds and cancellations datasets are critical to strictly define the target variable and quantify the economic impact of the phenomenon.

To facilitate analysis, a Python script was employed to normalize the nested JSON structures into Pandas dataframes. Following normalization, a critical feature engineering phase was executed. This step was designed not merely for data cleaning, but to operationalize theoretical concepts identified in the literature review. Specifically, derived temporal variables were calculated to measure behavioral patterns:

- **Lead Time:** calculated as the interval between the booking timestamp and the match start time. This variable is essential to test the findings of Illhet and Klein (2011) regarding the impact of booking horizons.
- **Cancellation Window:** defined as the duration between the cancellation timestamp and the scheduled start time, enabling the analysis of ‘last-minute’ behaviors described by Chen (2016).

Data cleaning procedures were also applied. Duplicate records were eliminated, and categorical inconsistencies (e.g., standardizing terminology such as ‘canceled’ vs. ‘cancelled’) were resolved. Missing values were audited and, rather than being indiscriminately removed they were retained, preserving the integrity of the datasets for the subsequent diagnostic analysis.

Several data integrity issues and inconsistencies were also identified and addressed. These included the removal of refund records that were not associated with any match, cases in which users without confirmed accounts were able to book matches, which were treated as confirmed for consistency purposes, and multiple cancellation requests for the same match, for which only the most recent request was retained. Additionally, cancellation requests that did not reference any match were removed, while requests marked as failed but linked to matches that were effectively cancelled were reclassified as accepted. Last, matches with a cancelled status but without any recorded cancellation request were retained, under the assumption that the match had indeed been cancelled despite the absence of an explicit request from an user, since it could be cancelled by FIELD itself without the need of creating a request. An exploratory data analysis was conducted for each dataset in order to gain initial insights into the data.

Finally, two additional datasets were incorporated to enable more detailed analysis if required. A Calendar dataset, spanning from 2019 to 2025, was generated not only to provide standard date keys but to capture critical temporal effects on leisure behavior. By integrating the Nager.Date API, national holidays in Portugal were mapped, along with derived features such as bridge days, seasons, and long weekends. Simultaneously, a Weather dataset was constructed using the Meteostat library (covering 11-02-2019 to 31-12-2025) for multiple relevant cities. Given that sports field rentals are largely dependent on outdoor conditions, meteorological variables such as temperature (avg, min, max), precipitation, wind speed, and sunshine duration were retrieved. This integration allows for

a possible assessment of environmental constraints as direct drivers of cancellations, specifically regarding the likelihood of attendance in adverse weather conditions.

3.2 Data Integration

Following the processing and preparation of the datasets, establishing the relational structure was a prerequisite for constructing the Star Schema in Power BI. To this end, a conceptual model was developed to visualize the entities (not yet including calendar and weather), attributes (with some of them aggregated for a clear visualization) and all the relationships between them.

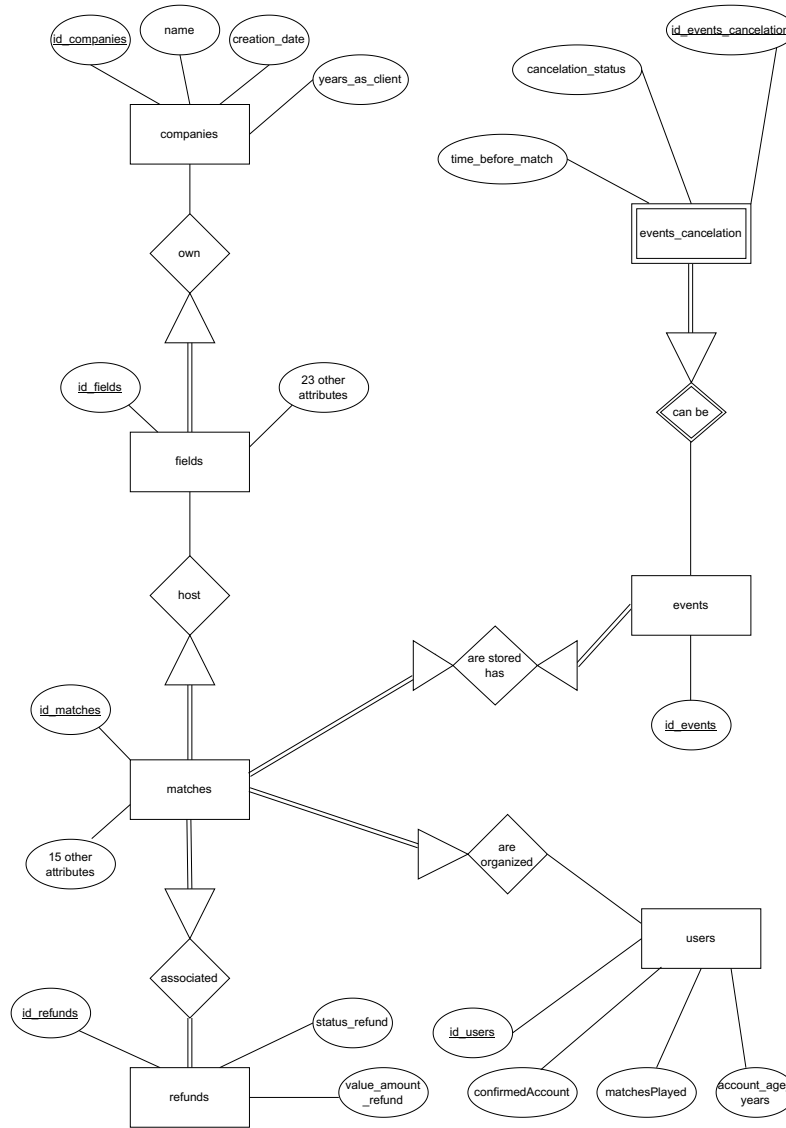


Figure 2: Conceptual Model

The analysis of cardinalities and functional dependencies within this model (presented above) highlights the centrality of the ‘matches’ entity. As it represents the core business event where primary metrics are recorded, it validates the selection of this entity as the Fact Table. Furthermore, it holds the necessary foreign keys to bridge the dimensions of “who booked” (users), “where it was booked” (fields), and the financial outcomes (refunds). Another critical design decision concerned the definition of the grain of the Fact Table, which was established at the lowest level of atomic detail: a

single row representing one individual match. This approach was prioritized over aggregated alternatives (such as daily or venue-level summaries) for distinct analytical reasons. Compared to an aggregated model, the atomic grain is superior as it preserves the necessary fidelity to calculate precise behavioral metrics. With this atomic granularity its possible to ensure that each record retains specific links to the Dimensional Tables, with this ones providing the essential descriptive context and characteristics for the fields, companies, users, refunds and cancellations.

A significant aspect during this modeling phase concerns the structural definition of the events entity. In the context of the operational database, events appeared to function, as mentioned before, as a composite sub-collection emerging from the intersection of matches and fields, essentially capturing the instance where a match is scheduled for a specific field as a distinct event with a unique ID event. However, after analyzing the relational dependencies, this entity in the conceptual model connects exclusively to the matches table, serving strictly as a structural link between matches and events cancellation. With these structural definitions established, the conceptual model was translated into the Star Schema, with the inclusion of calendar and weather. The tables were extracted from VS Code in CSV format and imported into Power BI.



Figure 3: Star Schema

The architectural design of the data model adheres to the Star Schema principles. This structural choice was deliberately prioritized following the guidelines of Kimball and Ross (2013), who argue that dimensional modeling provides the optimal balance between query performance and semantic clarity. By denormalizing data into a central fact table surrounded by descriptive dimensions, the model ensures that the system remains intelligible for non-technical managers while facilitating fast retrieval of aggregations.

The schema contains eight relationships, which are:

- Many-to-Many: **fields_final** to **weather_final** by column *city*
- One-to-One: **matches_final** to **cancellation_final** by column *id_events*
- Many-to-One: **fields_final** to **companies_final** by column *id_companies*

- Many-to-One: **matches_final** to **fields_final** by column *id_fields*
- Many-to-One: **matches_final** to **refunds_final** by column *id_matches*
- Many-to-One: **matches_final** to **users_final** by column *id_users*
- Many-to-One: **matches_final** to **calendar_final** by column *startDate*
- Many-to-One: **weather_final** to **calendar_final** by column *date*

In this specific context, the Many-to-Many relationship between fields and weather represents a conscious deviation from the classic Star Schema behavior. It allows a single field to be associated with multiple weather conditions over time, while a distinct weather record applies simultaneously to multiple fields in the same city. While the Power BI engine handles this cardinality to enable cross-filtering, it is acknowledged that this approach simulates a complex join and requires careful handling in measure calculation to avoid ambiguity in aggregation, contrasting with the simpler, unidirectional flow of standard dimensional relationships. Regarding One-to-One relationships, this cardinality is observed between matches and cancellation. Following the data processing phase, it was defined that each match can be associated with zero or exactly one cancellation record. Technically, this relationship is implemented referring to a Left Outer Join and by defaulting to this behavior, Power BI ensures that the analysis retains all records from the matches table, regardless of whether a corresponding cancellation record exists, allowing for a complete view of all scheduled matches. Many-to-One relationships are the most prevalent in the schema, primarily connecting the matches Fact table to the Dimension tables. This structure dictate that each match links to a single specific field, refund status, user, and date. With this configuration, the analytical engine assumes a directional flow from the dimension side to the fact side. Similar to the Left Outer Join logic applied before, this setup preserves the integrity of the data because if a record in the matches table references a dimension member that not exist (e.g., a missing User ID), Power BI preserves the match record rather than excluding it, categorizing the missing dimension as a blank or unknown value to maintain the accuracy of the total volume of analysis.

Ultimately, these relationships constitute the core of the analytical data model, providing more than just a structural basis for aggregation. Strategically, this architecture establishes the empirical foundation required to address the Research Questions (SQs). The strict enforcement of these relational constraints ensures that the subsequent Decision Support System (DSS) is fed with consistent data,

and the visualization layer gains the reliability needed to accurately isolate and display the drivers of cancellation.

4 Data Visualization and Decision Support System Development

4.1 Methodological Design Principles and Solution Architecture

The transition from data engineering to the development of the visualization layer was structurally guided by the Data-Information-Knowledge-Wisdom (DIKW) hierarchy, as described by Ward et al. (2019). This framework is particularly relevant to this study as it establishes that the efficacy of a Business Intelligence solution relies heavily on its ability to reduce cognitive load and accelerate interpretation. Crucially, the progression from raw data to actionable wisdom is not automatic. The Decision Support System (DSS) functions as the essential technological mediator in this process, synthesizing datasets into a coherent narrative. While Schelling et al. (2021) originally framed this DSS architecture within the context of sports injury prevention, this thesis conceptually transposes their framework to the domain of facility management. In this adapted model, the ‘injury’ to be prevented is recontextualized as the cancellation of a booking, requiring similar diagnostic. The selection of Power BI aligns strategically with the paradigm of Self-Service Business Intelligence (SSBI) rather than mere technical convenience. According to Passlick et al. (2020), organizational adoption of BI tools is heavily dependent on perceived flexibility and user autonomy. Power BI addresses these requirements through its native interactivity (cross-filtering and drill-down), which empowers non-technical users to navigate directly from high-level aggregations to granular root causes, ensuring the effective exploration essential for a DSS.

To address the complexity of the data without overwhelming the end-users, the reporting solution was structured into three distinct hierarchical levels, aligned with the needs of the company. Ward et al. (2019) emphasize that the relevance of information changes depending on the user’s role within the organization, and since the tool is going to be used by the operations team the architecture was segmented to serve their perspectives, while also offering possible strategic information. Regarding the first dashboard, this contains a General overview, designed to show the main metrics and information before allowing the user to navigate into two specialized analytic environments, the Matches view and the Fields view, with the three of them including diverse time factors. This type of organization ensures that the central research question can be answered, together with the

subsequent sub-research questions.

4.2 Analytical Components and Visualization Layers

A unified header structure was implemented across all three dashboards, featuring two primary Key Performance Indicators, Cancellation and Refund Rates, alongside temporal and spatial slicers (Year, City, Fields). The spatial arrangement of these elements adheres to the F-Shaped Pattern (Nielsen, 2006). The strategic placement of high-priority metrics in the top-left quadrant, followed by filtering controls, directly aligns with natural scanning behaviors. This layout strategy effectively minimizes cognitive load, ensuring that critical diagnostics are prioritized and processed instantaneously before the user navigates to the secondary visualizations in the lower quadrants.

4.2.1 General View

The General View works as the initial part of the understanding process, made to identify macro-drivers that might influence cancellation behaviors. Its primary analytical objective is to distinguish between systemic trends and isolated anomalies across four key dimensions: temporal, operational, typological, and spatial.

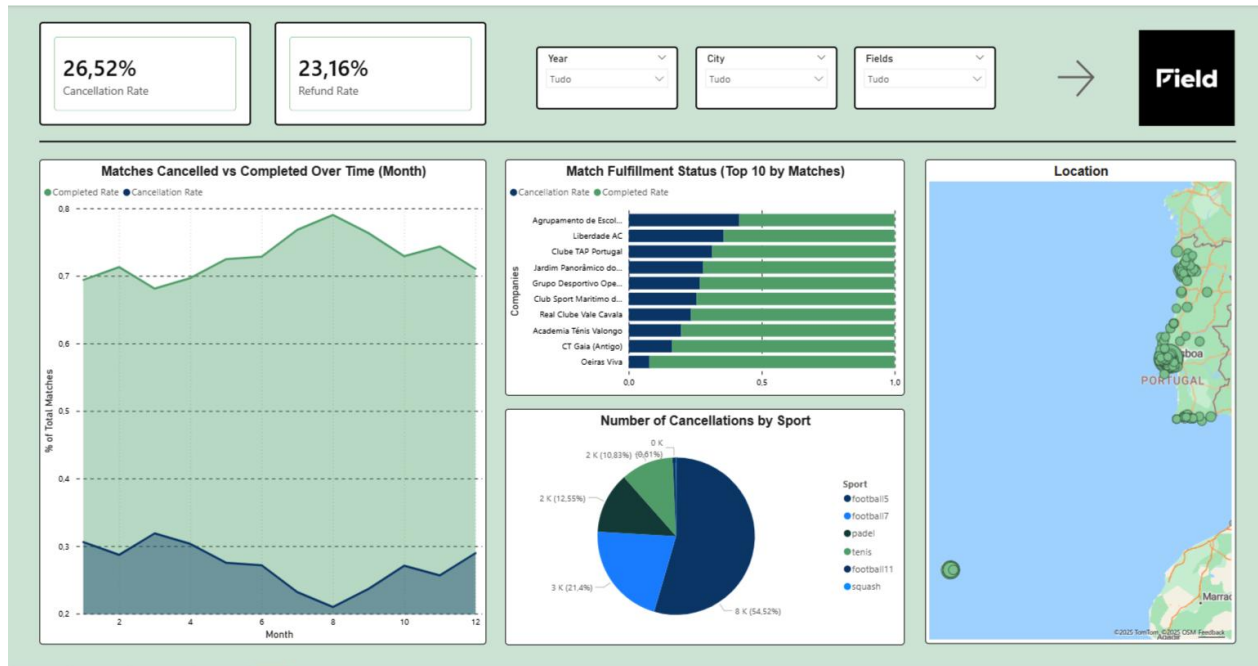


Figure 4: General View

To assess the impact of seasonality, a temporal evolution analysis tracks the ratio of completed versus cancelled matches throughout the year. This visualization is critical for determining if specific months act (e.g., winter months) as drivers for higher cancellation rates. Simultaneously, the operational dimension is scrutinized through a comparative analysis of the top 10 fields per matches scheduled showing its cancellation proportions, allowing for the immediate identification of specific partners that deviate from the norm.

Regarding activity typology, the analysis breaks down risk by sport. As evidenced in the aggregated data, this allows for the identification of specific modalities that exhibit a higher propensity for cancellations compared to others. Finally, the spatial dimension is addressed through a geospatial visualization, enabling the detection of regional ‘hotspots’, utilizing coordinate data to reveal if cancellations are clustered in specific geographic areas.

4.2.2 Matches View

The Matches View dashboard shifts the analytical focus from macro-drivers to the specific match characteristics of the booking itself. The objective here is to deconstruct the decision-making pro-

cess through three critical lenses: planning horizons, policy adherence, and economic sensitivity.

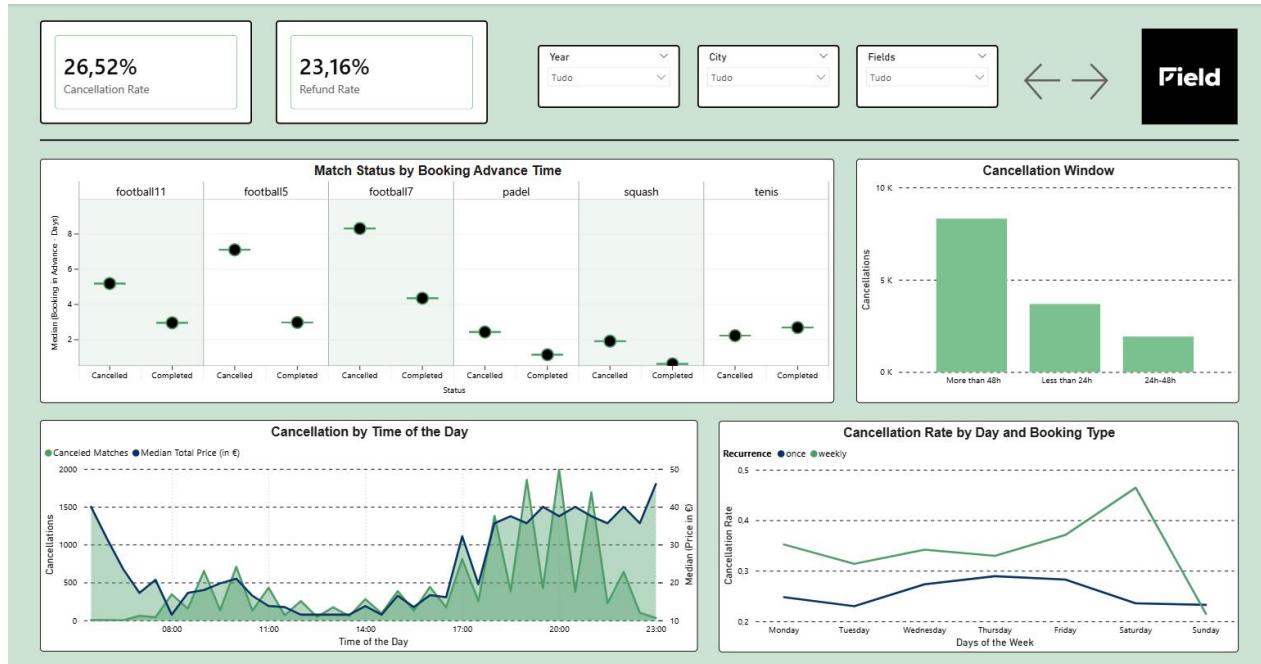


Figure 5: Matches View

To investigate the impact of advance planning, the analysis of Lead Time utilizes distribution metrics to compare the booking horizons of cancelled versus completed matches. This approach is essential to verify if longer planning periods introduce a higher degree of uncertainty, essentially testing the hypothesis that increased distance from the match causes a higher probability of cancellations and no-shows.

Complementing this, the Cancellation Window analysis investigates the precise timing of the cancellation decision relative to the match start. This metric serves as a direct diagnostic tool for evaluating policy effectiveness, revealing potential strategic behaviors where users might time their cancellations specifically to avoid financial penalties (e.g., cancelling immediately before a 48-hour refund cutoff). Furthermore, the interplay between Price and Time is scrutinized to detect sensitivity thresholds. The simultaneous visualization of hourly cancellation volumes and average pricing allows for the isolation of specific time slots or price points that act as friction factors.

In the bottom right corner, the analysis scrutinizes the impact of recurrence on reliability. The specific objective is to determine whether users with fixed ‘Weekly’ schedules exhibit a higher propen-

sity to cancel compared to clients who make spontaneous, single-instance reservations (‘Once’). This type of segmentation allows for a direct comparison of risk profiles.

4.2.3 Fields View

The Fields View constitutes the third analytical layer, shifting the diagnostic scope from the event to the physical asset. This dashboard addresses the sub-research questions regarding infrastructure, aiming to isolate how specific facility attributes and perceived quality act as structural drivers of cancellation.

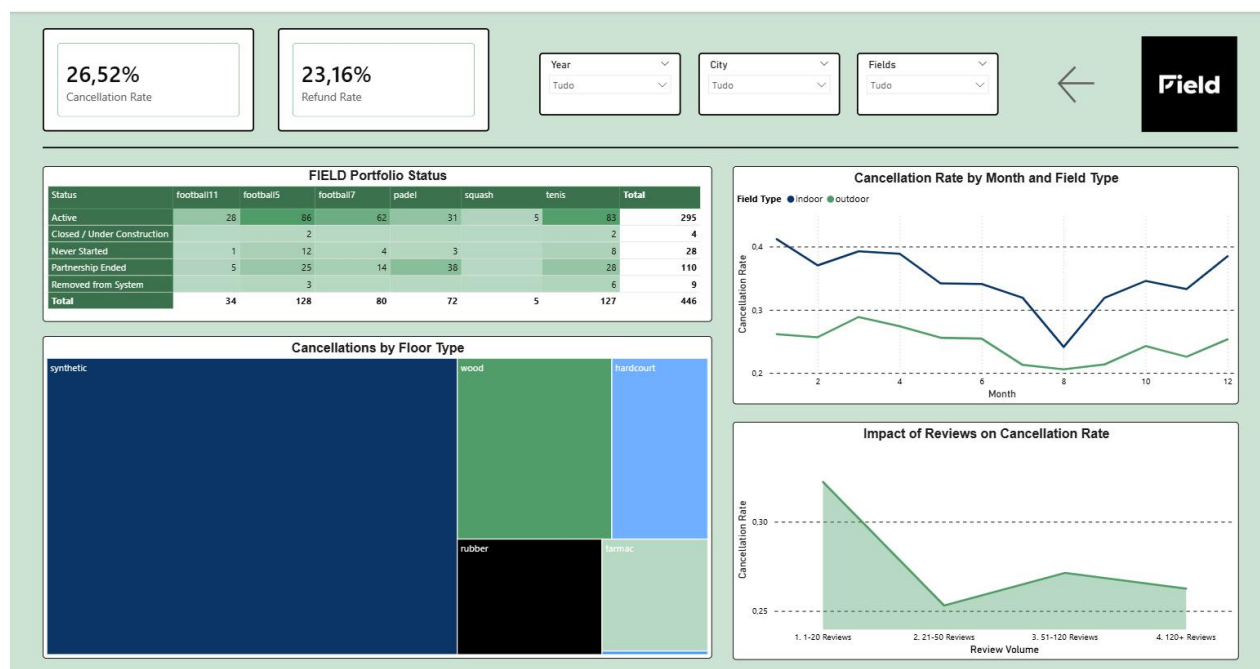


Figure 6: Fields View

The analysis begins by evaluating portfolio health, categorized by sport. Beyond a simple inventory list, this section scrutinizes the status of the supply side, identifying the specific reasons for field inactivity. This provides the necessary context to understand in which type of sport the company is losing partnerships.

Another critical component of this view is the assessment of external environment. By comparing cancellation between Indoor and Outdoor facilities throughout the year, the objective is to isolate the impact of external conditions (e.g. weather). This allows to understand if the cancellation volume

is attributable to the type of field. In addition, the technical attributes of the fields are examined through the connection between Surface Type (e.g., synthetic grass, wood) and disruption rates. This visualization permits a rapid diagnostic of which specific floor characteristics are most associated with booking failures.

In the end, the dimension of perceived quality is tested by analyzing the relationship between facility reputation and reliability. Segmenting fields into ‘Reputation Groups’ based on review volume helps to verify if established facilities benefit from having more opinions regarding cancellations.

4.3 Synthesis and Business Implications

The development of these dashboards culminates in an comprehensive Decision Support System that directly addresses the research objectives defined at the beginning of this study. Integrating the three views helps the company to move beyond reactive monitoring, just using an operational database, to a proactive management. This shift allows for the operationalization of the Data-Information-Knowledge-Wisdom (DIKW) hierarchy, where visualizations are not merely descriptive but serve as the foundation for data-driven decisions that identify and mitigate the drivers of cancellations.

4.3.1 SQ1: Match Characteristics as Drivers

Key Insights:

- **Aggregated Analysis:** the General overview establishes 5-a-side Football as the primary volume driver for disruptions, accounting for more than half of all cancellations. Behaviorally, the Matches View highlights a paradox regarding planning: with the exception of Tennis, cancelled matches are typically booked with a longer Lead Time (more days in advance) than completed matches. This aligns with findings in revenue management literature (e.g., Illhet & Klein, 2011), which suggest that longer booking horizons introduce higher temporal uncertainty. Furthermore, the analysis of the Cancellation Window reveals that a significant portion of cancellations occurs more than 48 hours before the match. This validates the strategic behavior described by Chen (2016), where users “hold” options and cancel just before the

penalty threshold, exploiting the policy window. Additionally, the prime-time window (18h to 21h), which commands the highest prices, registers also the highest volume of cancellations. Regarding recurrence, “Weekly” bookings show a high propensity for cancellation, particularly on Saturdays (approx. 46% rate).

- **Detailed Analysis:** applying filters for 2024 and 2025 exposes distinct regional nuances. In Lisbon, Football 5 is the dominant issue, with cancellations from this sport representing 65.2% in 2024 and rising to 70.96% in 2025. Conversely, in Porto, the problem is almost exclusively centered on Tennis, accounting for over 90% of cancellations in 2024 and reaching 99% in 2025.

Business Implications:

- **Revenue Instability:** the link between long lead times and high cancellation rates can create a significant strategic blind spot. FIELD cannot reliably count a value of a booking as a secured revenue for early bookings, distorting financial expectations.
- **Erosion of Prime-Time Bookings:** the behavior of booking well in advance and cancelling closely to 48 hours before notice highlights an operational inefficiency. High-demand slots are effectively blocked from the market for days, only to be released back when demand may have already shifted, representing a significant opportunity cost.
- **Full Capacity Inefficiency:** related to the first implication, but focusing on the operational side, when users book days in advance and cancel with 48h notice, they effectively block slots that can happen not to be sold again afterwards leading to an opportunity cost.
- **Modality-Specific Volatility:** rather than a generic market risk, the company faces distinct volatility profiles based on sport type. The extreme skew towards Tennis in Porto and Football 5 in Lisbon suggests that revenue stability is not uniform, but tied to the specific consumption habits of each modality, creating fragmented risk pools.

4.3.2 SQ2: Field Attributes as Drivers

Key Insights:

- **Aggregated Analysis:** in 2025, the active portfolio counts 293 fields but is heavily weighted towards Football and Tennis. An important finding is the lost of partnerships, evidenced by the loss of Padel fields (inactive count surpassing active count), suggesting the existence of more competitors in this market. Unexpectedly, the Fields View indicates that the cancellation rate for Indoor fields is consistently higher than Outdoor fields across all months. This contradicts the possible assumption that weather protection guarantees reliability. Additionally, fields with low reputation scores (1–20 reviews) suffer the highest cancellation rates (32%), establishing a link between perceived quality and booking commitment.
- **Detailed Analysis:** two specific cases identify direct problems. First, the most booked field in 2025, “Onze Unidos”, sustains a critical cancellation rate of 44%, implying that nearly half of the scheduled revenue coming from this field is at risk. Second, regarding surface types, games played on wood flooring present an alarming 65,97% cancellation rate, significantly higher than synthetic turf, despite the latter having higher volume of cancellations.

Business Implications:

- **Portfolio Volatility:** the instability in Padel fields suggests a vulnerability. If partners frequently leave the company for some reason (e.g. better options or features offered), it can trigger cancellations that are external to customer behavior, making growth projections difficult.
- **High-Risk Identification:** high-volume partners like “Onze Unidos” create a deceptive reality of success. While they generate high booking traffic, their disproportionate cancellation rate (44%) can transform them into an operational problem due to the high volume of refunds. This reflects the “net vs. gross” revenue dilemma often discussed in service management (Wirtz & Lovelock, 2021).
- **Infrastructure Dependency:** the extreme cancellation rate on wood flooring suggests that customers may be rejecting specific facility conditions (e.g. poor maintenance) rather than the sport itself. This highlights a vulnerability where the company suffers revenue loss due to external quality issues under the partner’s control, impacting the platform’s overall perceived quality.

4.3.3 SQ3: Location and Temporal Factors

Key Insights:

- **Aggregated Analysis:** geographically, cancellations are highly concentrated. The four main districts regarding field supply and match bookings (Porto, Lisbon, Faro, and Funchal) present a combined cancellation rate of 25.12% and a refund rate of 24.04%. Observing the location chart over the years, the “bubbles” shift from being scattered across the country to becoming increasingly concentrated in these specific districts, indicating a geographic contraction of the active portfolio. Temporally, the data indicates a seasonal pattern: cancellation rates drop slightly during summer months (correlated with lower match volume) and rise during winter months, likely driven by colder weather and reduced user willingness to practice sports. Historically, high cancellation rates were identified in 2019, 2020, and 2021 in diverse months (attributable to COVID-19 context). However, post-pandemic rates have stabilized between 20% and 30%, with current trends suggesting a potential decrease for 2025 (22.57% at the moment) compared to previous years. Regarding the weekly cycle, cancellation rates remain constant during weekdays but exhibit a significant spike on Saturdays, largely driven by the “Weekly” recurring bookings, as already mentioned. In terms of time of day, while prime-time slots lead in cancellations, there is a notable secondary peak in morning slots.
- **Detailed Analysis:** a drill-down into specific regions reveals diverging trends. Faro shows a positive evolution, having significantly reduced the number of cancelled matches over the years to a residual value in 2025. In Funchal, where a large portion of the platform’s inventory consists of Padel fields, specifically outdoor courts, as confirmed by the company, the inherent instability of the local weather leads to a consistently high number of cancellations.

Business Implications:

- **Concentration Risk:** the visual evidence that the company’s active portfolio is contracting into just four main districts (Lisbon, Porto, Faro, Funchal) exposes a critical concentration.

While these hubs generate volume, the reliance on them can create a “single point of failure” dynamic, if the number of cancellations increase.

- **Environmental Vulnerability:** the possible causality between winter months/outdoor fields in Funchal and high cancellation rates highlights a possible driver of cancellation. As noted by Falk and Vieru (2018) in hospitality, precipitation/cold weather can be a primary driver of cancellations.
- **Normalization of Inefficiency:** the fact that cancellation rates have stabilized between 20% and 30% post-pandemic suggests that FIELD is accepting that 1 in 4 bookings will not materialize, implying that the operational effort to manage bookings is around 25% less productive than it appears on paper. As noted by Kheirkhah et al. (2016) regarding appointment scheduling, high baseline no-show/cancellation rates inflate administrative costs (refunds, rescheduling).

5 Solution Validation and Utility Assessment

Following the construction of the tool, a validation phase was conducted in collaboration with the company's stakeholders. This stage was critical to ensure the Decision Support System alignment with business needs, established upon a dual objective: (i) to validate the usability of the DSS, ensuring the interface is intuitive and accessible for the end-users, and (ii) to evaluate its practical utility, assessing its effectiveness in supporting complex decision-making processes regarding cancellation drivers.

5.1 Participants Profile

The validation process involved three stakeholders, selected based on specific criteria to represent the typical end-user profile within the operational context: professionals with domain knowledge but limited technical expertise in data analytics. This selection strategy was deliberately aimed at assessing the solution's intuitiveness without the interference of prior technical proficiency bias. Regarding their familiarity with Business Intelligence tools, a preliminary assessment was conducted where all participants were explicitly asked about their previous experience. The results confirmed their eligibility for this test: two participants reported having no prior contact with Power BI or similar platforms, while the third indicated only very limited experience many years ago.

- **Business Operations Manager:** the primary end-user, responsible for field support and operational tasks. This stakeholder assessed the DSS's capability to transform data into actionable insights, focusing on the clarity of information for day-to-day management.
- **Head of Tech:** technical lead of the development team, responsible for database maintenance and integrity. This stakeholder focused on data accuracy and evaluated how the DSS automates reporting workflows, thereby reducing the overhead of manual reporting
- **Chief of People and Operations:** acts as the bridge between business requirements and technical capabilities. Evaluated the DSS from a management perspective, assessing its potential to close the gap between operational needs and development feasibility, while ensuring strategic alignment.

5.2 Task-Based Testing and Think Aloud Protocol

To simulate a realistic operational environment, a Task-Based Usability Testing approach was implemented, using Time-to-Insight (the duration between reading the task and successfully verbalizing the correct answer) as the primary performance metric. This metric serves not only as a measurement for operational and interpretability speed but also for cognitive clarity, measuring how effortlessly the user can translate visual data into understanding. As defended by Jooste et al. (2014) in the context of BI evaluation, simply measuring navigation is not sufficient, it is critical to assess the user's ability to derive meaning.

The testing protocol was structured with 15 specific tasks, a quantity designed to ensure comprehensive coverage of all the DSS functionalities. The distribution was balanced to validate all components: 4 tasks focused on the first dashboard, 4 on the second, 5 on the third, and 2 complex scenarios where the user was required to autonomously determine which dashboard to utilize, thereby testing cross-report navigation. During execution, a Think-Aloud Protocol was also employed, where participants were instructed to verbalize their thought processes to identify UX/UI improvement points. For the purpose of the analysis, the Business Operations Manager is referred to as Stakeholder A, the Head of Tech as Stakeholder B, and the Chief of People and Operations as Stakeholder C.

Table 1: Task-Based Usability Testing Results

ID	Task Description	STK A	STK B	STK C
1	Determine the Cancellation Rate for the district of Setubal.	0m 18s	0m 43s	0m 14s
2	Identify the sport with the highest number of cancellations in the district of Faro.	0m 44s	0m 37s	0m 10s
3	Discover which month, specifically in 2024 across all districts, had the highest cancellation rate.	0m 55s	0m 52s	0m 31s
4	What is the name of the company with the fourth-highest number of scheduled matches in that specific month?	0m 36s	0m 23s	0m 50s
5	Identify for which sports cancelled matches were booked with a longer lead time than realized matches.	0m 41s	2m 13s	0m 50s
6	Identify at which hour of the day the highest number of cancellations occur.	0m 24s	0m 21s	0m 10s
7	What is the time window in which the most matches are cancelled?	0m 08s	1m 35s	0m 10s
8	In the Lisbon district (2023), is the cancellation rate higher for 'Once' or 'Weekly' bookings on Saturdays?	0m 45s	1m 07s	0m 42s
9	Identify the month of the year where the cancellation rate for 'Outdoor' fields is highest.	1m 01s	0m 57s	0m 27s
10	Determine which Floor Type records the second-highest absolute number of cancellations.	0m 20s	0m 08s	0m 14s
11	Discover the primary reason listed for inactive fields no longer being part of the company portfolio.	0m 36s	0m 43s	0m 10s
12	Identify the sport that currently has the highest number of active fields in the network.	0m 16s	0m 28s	0m 25s
13	Analyze if fields with more reviews (+120) effectively have a lower cancellation rate than fields with fewer reviews (1-20).	0m 47s	0m 31s	0m 14s
14	What is the cancellation rate of the company with the highest volume of scheduled matches in 2025?	1m 56s	2m 20s	0m 34s
15	How many active fields exist in total where the Floor Type is synthetic?	1m 25s	0m 16s	0m 53s

To ensure a structured analysis, observations were classified into distinct dimensions: Performance Overview, UX/UI Design (interface legibility and layout), Analytical Interpretation (cognitive load and graph comprehension), and Task Formulation/Strategic Feedback (clarity of the testing script).

• **Stakeholder A (Business Operations Manager)**

Performance Overview: demonstrated rapid adaptation to the platform's interface, navigating easily through the General Dashboard (Tasks 1–4) with no significant usability blocks.

Analytical Interpretation Issues: task 3 recorded a slightly higher Time-to-Insight (0m 55s). The Think-Aloud process revealed that this delay was caused by the cognitive load required to interpret

the Line Chart, where months were represented numerically (1-12). The user suggested replacing these with full month names to accelerate data interpretation.

UX/UI Design Issues: in the Fields dashboard, Task 9 highlighted a TTI of 1m 01s, attributed to difficulty in locating the “Outdoor vs. Indoor” distinction within the visual, indicating a clear need to increase font size for better legibility.

Task Formulation/Navigation: a specific issue arose in Task 5, where the user expressed initial confusion regarding the phrasing of the question itself, rather than the tool. Additionally, Tasks 14 and 15 registered the highest TTI values (>1 min), but this was an anticipated result of the test design, which required the user to autonomously search for the correct dashboard without guidance.

Overall, Stakeholder A validated the DSS’s alignment with business needs, explicitly confirming that the insights gathered would effectively support daily operational decision-making.

- **Stakeholder B (Head of Tech)**

Performance Overview: showed efficient completion of initial tasks but provided valuable technical feedback on the user experience.

Analytical Interpretation Issues: a significant spike in TTI was observed in Task 5 (2m 13s) regarding the Box Plot in the Matches dashboard. While acknowledging the high value of this visualization for understanding lead times, the stakeholder noted that the statistical concept was initially complex to interpret without prior context.

UX/UI Design Issues: as the test progressed to the Fields Dashboard, TTI values improved, but a usability improvement point was identified in Task 14. The user struggled to distinguish whether the “Top 10 Companies” chart referred to total scheduled matches or cancellations. This ambiguity highlighted the need for a more descriptive chart title or clearer axis label. The user also suggested general UX improvements, such as increasing the size of filters and titles.

Although not the intended daily user, Stakeholder B confirmed that the visual accessibility of the data represents a substantial upgrade over the current workflow based on operational databases.

- **Stakeholder C (Chief of People and Operations)**

Performance Overview: was the fastest participant to complete the tasks, demonstrating deep business knowledge and intuitive navigation in the final unguided tasks (14 and 15).

Analytical Interpretation Issues: similar to Stakeholder B, Task 5 resulted in a longer response time (0m 50s). The user found the Box Plot interesting but required a brief explanation to fully understand the visual logic. Conversely, in Task 7, the user praised the dual-axis chart, noting the high utility of seeing peak cancellation hours alongside the associated monetary loss.

Strategic Feedback: this financial awareness prompted a specific suggestion in Task 12. The matrix could benefit from aggregating fields by “Parent Company” to better assess the risk of losing multiple fields if a single partnership is terminated.

This stakeholder validated the system’s intuitive nature and contributed with high-level strategic suggestions for future data modelling.

- **Future Iterations and Continuous Improvement**

It is important to conclude that the feedback collected via the Think-Aloud Protocol extends beyond validation as it serves as an identification for a next development cycle of the DSS. The identified suggestions are not considered failures, but rather opportunities for future iterations.

5.3 System Usability Scale

Complementary to the Task-Based Usability Test, a quantitative assessment was conducted using the System Usability Scale (SUS), an industry-standard ten-item questionnaire that generates a composite usability score ranging from 0 to 100.

To interpret the results effectively, this thesis relies on the benchmarking guidelines established by Lewis (2018), determining a SUS score of 68 as the center of distribution (50th percentile). Therefore, any score exceeding 68 is statistically considered “above average”, while scores surpassing 80 are typically classified as excellent.

Table 2: System Usability Scale (SUS) Results

ID	SUS Question	STK A	STK B	STK C	Mean	St. Dev.
1	I think that I would like to use this system frequently.	5	5	5	5.00	0.00
2	I found the system unnecessarily complex.	2	2	1	1.67	0.58
3	I thought the system was easy to use.	5	5	5	5.00	0.00
4	I think that I would need the support of a technical person to use this.	1	1	4	2.00	1.73
5	I found the various functions in this system were well integrated.	5	4	5	4.67	0.58
6	I thought there was too much inconsistency in this system.	1	1	1	1.00	0.00
7	I would imagine that most people would learn to use this system quickly.	5	5	5	5.00	0.00
8	I found the system very cumbersome to use.	2	1	1	1.33	0.58
9	I felt very confident using this system.	5	4	5	4.67	0.58
10	I needed to learn a lot of things before I could get going with this.	1	1	1	1.00	0.00

Table 3: System Usability Scale (SUS) Scores

Participant	Professional Profile	SUS Score (0-100)
Stakeholder A	Business Operations Manager	95.0
Stakeholder B	Head of Tech	92.5
Stakeholder C	Chief of People and Operations	92.5
Average Score		93.3

As shown in the tables, the quantitative assessment reaches a global average SUS score of 93.3. When benchmarked against the standard distribution curve defined by Lewis (2018), this result places the DSS in the top percentile of usability, significantly surpassing the 80-point threshold required to achieve an excellent classification.

- **Stakeholder A (Business Operations Manager)** awarded the system a near-perfect score of 95.0. This high rating is particularly significant given the user's lack of prior experience with Business Intelligence platforms. It strongly suggests that the dashboard successfully abstracts the complexity of the underlying data, offering a clear overview of the business status.
- **Stakeholder B (Head of Tech)** recorded a score of 92.5, classified as excellent. This high score validates the system's efficiency in reducing the workload, transition from manual database management to an automated visual interface.

- **Stakeholder C (Chief of People and Operations)** rated the system at 92.5. Given this user's role, this result provides evidence that the developed tool offers not only important points for day-to-day operations but also touches upon strategic points of the company.

5.4 Final Answer to Research Questions

It is important to note that, while the insights presented in the Section 4 strategically prioritized high-impact dimensions - specifically data from 2024 and 2025 and the districts with the highest volume of operations - the utility of the Decision Support System (DSS) extends far beyond this scope. The interactive nature of the tool allows for the continuous exploration of niche markets or historical patterns through its dynamic slicers, ensuring its relevance as the business context evolves.

The implementation of this DSS marks a fundamental shift from operational opacity to strategic clarity. What was previously obscured by aggregate averages is now visible: the realization that secured revenue from early bookings is highly volatile, that recurring weekly slots mask a lack of commitment, and that specific partners act as structural drains on profitability. This distinction is crucial. Before the DSS, FIELD could only observe that cancellations were happening. Now, they understand why they happen and where to intervene. This transformation validates the primary research question, demonstrating that the drivers of cancellation are not random, but identifiable and measurable, as well as the sub-research questions that supported it. By converting raw data into these actionable diagnostics, the study effectively completes the hierarchical cycle proposed by Ward et al. (2019), which encompasses moving beyond the mere accumulation of Information and Knowledge about cancellation rates, to the attachment of the Wisdom required to mitigate them proactively.

Furthermore, the consistency of high scores presented in SUS confirms the tool's usability, but also adaptation to FIELD organizational context. This achievement is particularly relevant when framed against broader findings in software usability research. For instance, Vlachogianni and Tzafilkou (2022), in a systematic review regarding the application of SUS in complex digital platforms, indicate that average usability scores typically fall significantly below the 80-point mark. Consequently, obtaining a mean score of 93.3 is a positive outlier that places this Decision Support System in a tier rarely observed in functional software evaluations.

6 Conclusion

This final chapter presents the key findings achieved throughout this master’s thesis, directly related to the Research Questions. It also outlines the contributions and practical implications of this work, both in the academic context and for FIELD, which will utilize the DSS in its business moving forward. I conclude by mentioning the main limitations encountered and indicating areas for future work.

6.1 Summary of Findings

The main goal of this dissertation was the construction of a Decision Support System capable of helping the company transform data that resided solely in the operational database, without analytical use, into tangible knowledge, enabling data-driven decisions regarding match cancellations. The development of the interactive Power BI dashboard, specifically the three implemented views, allowed this objective to be successfully achieved, effectively answering the research questions, from which the following findings are underlined:

- **Match Characteristics:** the findings reveal a clear “planning paradox”, with longer lead times acting as strong predictors of cancellation. Although they book early, users who cancel their games also cancel with relative anticipation, in this case more than 48h, in order to receive a full refund. Football 5 matches are the sport with more cancellations, being important to understand subsequent reasons for this number. The instability is further compounded by the type of scheduling. “Weekly” recurring reservations emerged as a critical vulnerability, driving a cancellation spike on Saturdays (approx. 46%), which suggests that users treat these recurring slots as flexible “options” rather than firm commitments. Additionally, the drivers of cancellation are geographically distinct, with Lisbon’s instability driven by Football and Porto’s by Tennis. Prime-time window (18h-21h) presents the highest number of cancellations, followed by the morning hours.
- **Field Attributes:** the study confirmed a portfolio supported mainly in Football 5, Football 7 and Tennis partnerships, with physical infrastructure and partner reliability significantly impacting cancellations of bookings. The surface type emerged as a vulnerability, with wood

flooring presenting disproportionately higher cancellation rates. The analysis of partner performance revealed specific cases where high booking volumes can be connected with high cancellation rates, leading to operational stress (e.g. high number of refunds to make) and difficulty in revenue prediction. Fields with a low number of reviews present a higher cancellation rate, suggesting that the users look to this information when booking or cancelling a reservation. Indoor fields present lower cancellation rates across all months, compared to outdoor fields, which can indicate that a possible driver regarding external environments is not related to the Type of Field, but yes to its location.

- **Temporal and Location Factors:** the results uncovered that cancellation behavior can be tied to temporal and geographic contexts. The dashboard exhibits a high concentration risk, reliant on four main districts where 1 in 4 matches is cancelled. Seasonality also plays a measurable role, with rates rising in winter months, a trend best exemplified by the case of Funchal, where Padel outdoor courts makes the revenue stream highly susceptible to local weather instability, being a possible driver for a great number of cancellations. The weekly cycle analysis corroborates the impact of recurring bookings, showing stable rates on weekdays but a significant spike on Saturdays. Longitudinally, the drivers have evolved: while 2019–2021 rates were influenced by the pandemic context, post-pandemic metrics have stabilized between 20% and 30%, with distinct regional trajectories, such as Faro, which, unlike Funchal, has successfully reduced its cancellation volume, to residual levels over the years.
- **Main Drivers of Cancellations and No-Shows:** regarding the central research question, this dissertation concludes that these events are not random occurrences but driven by a complex interplay of identifiable variables. The findings confirm that Match Characteristics, Field Attributes, and Temporal/Location Factors act as determinants of cancellation behavior.

6.2 Contributions and Practical Implications

This dissertation delivers dual contributions that bridge the domains of behavioral service operations and information systems. Academically, addresses critical gaps by expanding revenue management research beyond traditional hospitality sectors into high-turnover recreational sports. The literature

often prioritizes purely predictive models but this study challenges that prevalence by validating the importance of a diagnostic approach, isolating specific determinants of cancellations such as Match Characteristics, Field Attributes, and Location and Temporal context. In addition, the value of this thesis extends beyond the identification of these drivers. It also lies in the methodological application of Business Intelligence frameworks to operationalize these findings, adopting the layered modular approach defended by Ward, Windt, and Kempton (2019), demonstrating how data visualization serves as a connection between raw data and managerial action. The study provides a validated use case showing that in contexts of high uncertainty like sports facility management, the ability to visually diagnose root causes is as valuable as predicting outcomes.

For FIELD, these insights materialize in a custom Decision Support System. Validated as highly suitable for the organization's structure, this tool represents a tangible asset that empowers the company to transition from reactive to proactive risk management. Previously, manual analysis consumed significant time and delayed the identification of problems. The DSS resolves this latency and optimizes Time-to-Insight, which accelerates the path from metrics to actions, exposing the main drivers of cancellation and turning uncertainty into visible patterns.

6.3 Limitations and Future Work

This research was constrained by the proprietary nature of FIELD's data, which required strict confidentiality protocols. Additionally, reliance on the company's availability for data extraction created temporal disparities between the academic thesis deadline and the tool's technical development, with the need of a time management.

Regarding future work, it is suggested to leverage the already structured weather dataset to isolate environmental drivers. The logical next step is to evolve from diagnostic to Predictive Analytics, integrating algorithms to forecast the cancellation probability of specific matches directly within the dashboard. Finally, continuous UX/UI iterations are recommended to refine the interface according to the company's evolving operational needs.

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