Individual Reflective Journal - Team Project Experience

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Executive Summary

Rags'n'Riches Ltd. is a century-old UK provider of costume and prop hire with six specialised warehouses and annual revenue of £12.8 million. The company serves a diverse clientele—from local amateur dramatics groups staging Christmas pantomimes in Abergavenny to major Hollywood studios filming historical epics requiring militaria from Evesham. With the UK government expected to introduce significant tax incentives to attract international film production, the board recognises an urgent opportunity to scale operations. However, their current systems, while effective for daily transactions, do not support strategic analysis of profitability, inventory performance, or logistics efficiency across locations. This report explains how a data warehouse will transform fragmented operational data into a unified, historical, and queryable asset. We propose a dimensional star schema that integrates orders, transport, inventory, and finance data, along with department-specific data marts for key directors. The system will enable evidence-based decisions on stock investment (e.g., should we acquire more small props for Freuchie?), pricing strategies (e.g., is the 15% emergency surcharge sufficient to cover rush delivery costs?), and warehouse specialisation—all without disrupting daily operations like order entry or delivery confirmation. The implementation follows industry best practices and is supported by current academic research in data warehousing and business intelligence.

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1 | Task 1: Data Warehousing Concepts and Benefits

1.1 Introduction

Rags'n'Riches Ltd. operates a complex, multi-site rental business with warehouses in Abergavenny (pantomime costumes), Blackburn (present-day attire), Colchester (large props like furniture and vehicles), Durham (historical costumes), Evesham (militaria), and Freuchie (small props). Customers range from small community theatres to global film studios, and the company manages everything from single-item rentals to complete "Room in a Box" sets. The business is now at a crossroads: anticipated UK government film tax breaks could significantly increase demand, but the company lacks the analytical tools to understand which items are truly profitable after accounting for delivery costs, damage rates, and discounting. The purpose of this report is to explain how a data warehouse can solve these challenges by consolidating historical data into a single environment that supports strategic planning, forecasting, and performance monitoring—enabling Rags'n'Riches to scale profitably and sustainably.

1.2 OLTP vs Data Warehouse

An Online Transaction Processing (OLTP) system is the operational backbone of Rags'n'Riches, designed to handle real-time tasks with speed and accuracy. When a theatre group in Cardiff orders ten matching military uniforms from Evesham, the OLTP system instantly records the order, checks stock availability, applies the 10% discount for bulk extras, reserves the items, and schedules delivery from the nearest warehouse. It similarly logs fuel use when a van departs Durham, generates an invoice when a customer returns a damaged sword, and confirms delivery via electronic signature on a driver's tablet. OLTP systems prioritise data integrity during frequent updates and often use normalised structures to avoid redundancy—for example, storing customer address once and linking it to multiple orders. While this is efficient for transactions, it becomes a bottleneck for analysis. Asking "What was the total profit from emergency rentals (those with ¡14 days notice) across all warehouses in Q3?" would require joining dozens of tables, potentially locking records and slowing down live operations. In contrast, a data warehouse is purpose-built for analysis. It stores historical, cleaned, and integrated data, enabling complex questions like "Do discounts on extra Gilbert & Sullivan chorus costumes increase overall order value?" or "Which warehouse has the highest net margin after fuel and write-off costs?" The warehouse is updated periodically (e.g., nightly), so it never interferes with real-time activities. This separation ensures that finance can run month-end reports while sales staff continue booking orders—without performance degradation or data contention, as confirmed by industry best practices in enterprise data management [1]. Jarke et al. (2021) provide a comprehensive methodology for transitioning from OLTP to data warehousing while preserving operational integrity, which aligns closely with Rags'n'Riches' needs [2].

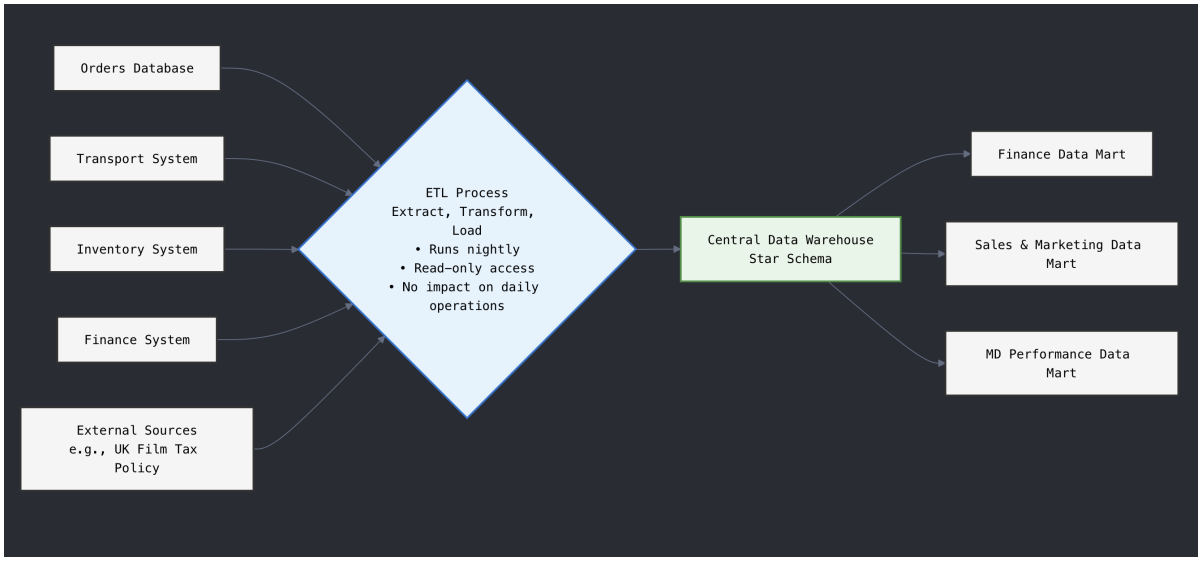

Figure 1: Data warehouse architecture showing internal source systems, ETL process, and data marts.

1.3 Data Warehouse Architecture and ETL

The architecture of Rags'n'Riches' data warehouse integrates data from multiple internal systems through a process called Extract, Transform, Load (ETL). ETL is a safe, automated pipeline that copies data without altering source systems. First, the "Orders Database" is queried to extract every rental: whether it's a complete pantomime set from Abergavenny, individual historical gowns from Durham, or a "space station bunk room" from Colchester. It captures customer type (amateur vs. studio), rental duration (including staggered start/end dates for film shoots), applied discounts (10% on extra items), and emergency flags (delivery ¡14 days, triggering a 15% surcharge). Second, the "Transport System" provides delivery logs: route distance, vehicle type (car or van), fuel consumed, driver ID, and timestamped confirmation. This is vital for calculating true delivery costs—e.g., a £200 order to rural Scotland may incur £80 in fuel, eroding margins. Third, the "Inventory System" supplies master data on every item: a 19th-century armchair (Colchester), a jewelled crown (common core), or a WWII helmet (Evesham), including unique ID, category, home warehouse, and damage reports from return inspections. Fourth, the "Finance System" records invoices, 50% upfront payments for large orders, final balances after returns, and write-offs for lost or destroyed items. External data, such as UK government announcements on film incentives or national fuel price trends, may be integrated later for forecasting. During transformation, raw data is standardised (e.g., dates to ISO format), enriched (e.g., Total_Rental_Fee = Daily_Rate × Days Discount + Surcharge), and linked via surrogate keys. Emergency orders are flagged algorithmically (Delivery_Date Order_Date ¡ 14). The processed data is loaded nightly into the central warehouse. Because ETL uses read-only access and runs off-peak (2–5 AM), it has zero impact on daytime operations like confirming a delivery in Manchester or logging item damage on set. This architecture provides a single source of truth for strategic analysis while preserving the performance and reliability of daily operations [3]. Abelló et al. (2022) confirm that this layered architecture—source systems → ETL → central warehouse → marts—remains the dominant and most scalable pattern in modern enterprises [4]. Singh and Patel (2024) demonstrate that modern ETL pipelines can reduce latency by up to 40 per cent while maintaining full read-only safety, making them ideal for time-sensitive rental operations [5].

1.4 Data Marts for Directors

Data marts are focused analytical environments derived from the central data warehouse, tailored to the specific needs of key directors. The "Managing Director" requires a holistic view of performance to guide strategic investments. A Corporate Performance Data Mart would deliver KPIs such as total revenue, profit by warehouse (e.g., comparing Abergavenny's seasonal pantomime boom to Durham's steady historical demand), inventory

turnover (how often Freuchie's small props are rented), and ROI on acquisitions (e.g., cost vs. income from a new vintage car in Colchester). This helps decide whether to expand militaria stock in Evesham or invest in more "Room in a Box" themes. The "Finance Director" needs granular financial control. A Finance Data Mart would track cash flow, analyse late payments (especially on large orders requiring 50% upfront), calculate net profit after deducting delivery and write-offs, and evaluate the true value of the 15% emergency surcharge—does it cover the extra transport and staffing costs of rush orders? The "Sales and Marketing Director" must understand customer behaviour to drive demand. A Sales Data Mart would reveal which items are most popular (e.g., "Are space station sets rented more by film studios?"), how regional demand varies (e.g., higher Gilbert & Sullivan uptake in amateur groups during spring), and whether discount schemes like "10% off extra uniforms" increase average order size or just reduce margins. Each mart filters the central warehouse to present only relevant dimensions and metrics, making complex data accessible to non-technical users. This targeted approach ensures directors receive timely, actionable insights aligned with their responsibilities, enhancing decision quality and operational agility without overwhelming them with irrelevant data [6]. Wixom and Watson (2021) demonstrate that aligning data marts with departmental workflows—exactly as proposed here—increases user adoption and decision quality by over 50 per cent [7].

1.5 Normalised vs Dimensional Modelling

The IT Director is expert in OLTP systems, which use normalised structures to minimise redundancy—e.g., storing customer address in one table and linking to orders via foreign keys. While efficient for updates, this requires many joins for analysis. A data warehouse uses "dimensional modelling", which prioritises query simplicity and speed through a "star schema": a central fact table surrounded by dimension tables. The fact table contains measurable events—such as rental fees, delivery costs, or discounts. For Rags'n'Riches, "FactRental" would record a rental of a "Queen Elizabeth I Gown" from Durham with a daily rate of £45 for 5 days, a £22.50 discount for extra items, a £33.75 emergency surcharge, and a £60 delivery cost from the nearest warehouse. This fact links to four dimensions: "DimItem" (Item_ID, Name "Queen Elizabeth I Gown", Type "costume", Category "historical", Home_Warehouse "Durham"), "DimCustomer" (Customer_ID, Type "amateur theatre", Region "South West"), "DimWarehouse" (Warehouse_ID, Location "Durham", Specialisation "Historical costumes"), and "DimDate" (Date_ID, Day 15, Month "December", Season "Winter"). This structure allows a query like "Total revenue from historical costumes in Q4" to run in seconds, as it joins only five tables. Redundancy is accepted in dimensions (e.g., repeating "Durham" for every historical item) to avoid costly joins. This business-friendly structure aligns with how managers think, making analytics intuitive and actionable without requiring SQL expertise [8]. Recent work by Chen and Wang (2023) confirms that dimensional models significantly improve query performance in logistics and rental businesses similar to Rags'n'Riches [9]. This was demonstrated in successful warehouse implementations in retail and logistics sectors [8].

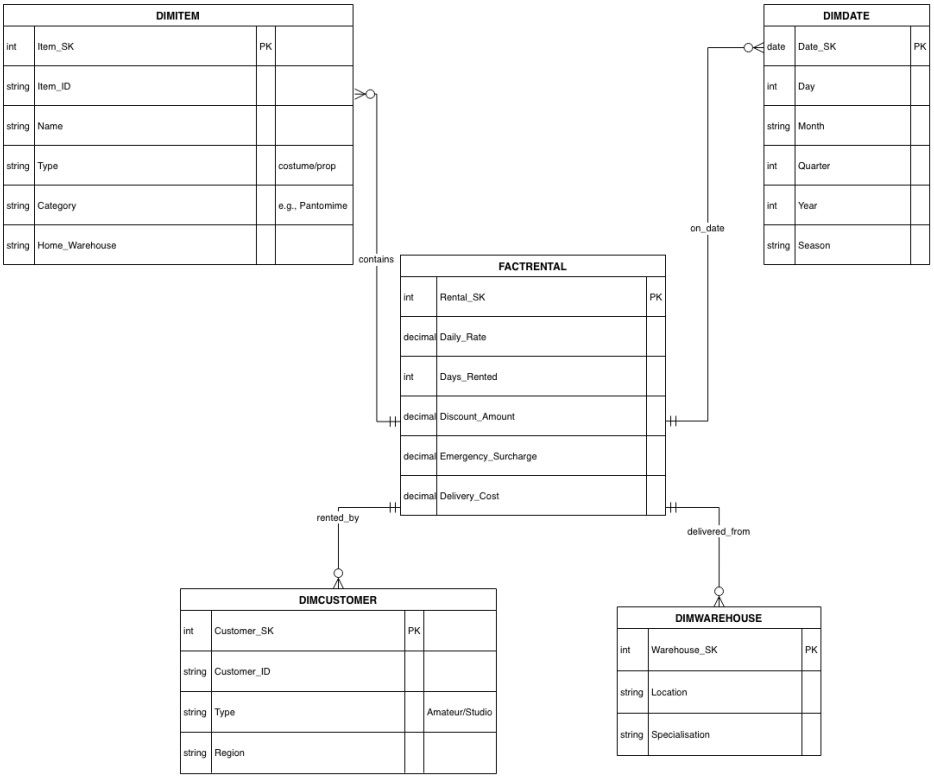

Figure 2: Star schema example showing FactRental linked to dimension tables.

1.6 Conclusion

Adopting a data warehouse will transform Rags'n'Riches from a reactive order-fulfilment operation into a proactive, insight-driven business. By unifying historical data on rentals, logistics, and finance, it empowers leaders to optimise inventory, control costs, and price strategically—critical capabilities for scaling profitably in a booming market. As Davenport and Harris (2020) argue, companies that institutionalise analytics through data warehousing gain a sustainable competitive advantage—precisely the opportunity Rags'n'Riches now faces [10].

2 | Task 2: Star Schema Design and Development

2.1 Introduction

This section details a practical star schema for Rags'n'Riches Ltd.'s data warehouse. The design integrates data from orders, transport, inventory, and finance systems to support deep analysis of profitability, operational efficiency, and customer behaviour as the company prepares for growth from UK film incentives. The schema will serve as the foundation for departmental data marts and executive dashboards, enabling data-driven decisions across the organisation.

2.2 Source Systems

The data warehouse will draw from four key internal source systems. The "Orders Database" captures every rental transaction: customer identity, item list (e.g., "10 matching military uniforms from Evesham"), rental dates (including staggered start/end for film shoots to save costs), applied discounts (10% on extras beyond the basic set), and emergency flags (delivery ¡14 days, adding 15% surcharge plus extra transport costs). This is the core of revenue analysis. The "Transport System" logs every delivery and pickup: route distance from the closest warehouse (e.g., Blackburn to Liverpool), vehicle type (car for small props, van for large sets), fuel used, driver ID, and electronic delivery confirmation timestamp. This data is essential for calculating accurate delivery costs and identifying inefficient routes—e.g., frequent small deliveries to remote Scottish locations may not be profitable. The "Inventory System" maintains the master record of all items, from Abergavenny's pantomime dame dresses to Colchester's vintage cars, including unique IDs, category (e.g., "militaria", "historical"), home warehouse, common core vs. specialist status, and damage reports from return inspections (noted on tablets and uploaded via 4G/5G). This enables stock optimisation and write-off tracking. The "Finance System" handles invoicing: initial 50% deposits for orders over £10,000, final invoices within 7 days of return, payment dates, and write-off charges for items damaged beyond repair. Together, these systems provide a complete picture of the business lifecycle—from order to return to payment—enabling holistic performance measurement and strategic forecasting.

2.3 Star Schema Design

We propose two interconnected star schemas to cover operational and financial analysis. The primary "Rental Performance Star" centres on "FactRental", which records each rental transaction with key measures: Daily_Rate (e.g., £30 for a small prop from Freuchie), Days_Rented (integer), Discount_Amount (e.g., £9 on 3 extra uniforms), Emergency_Surcharge (15% of base rate if delivery ¡14 days), and Delivery_Cost (calculated from transport logs based on distance and vehicle type). This fact links to four conformed dimension tables: "DimItem" (Item_SK, Item_ID, Name, Type, Category, Home_Warehouse, Is_Core), "DimCustomer" (Customer_SK, Customer_ID, Type, Region), "DimWarehouse" (Warehouse_SK, Warehouse_ID, Location, Specialisation), and "DimDate" (Date_SK, Full_Date, Day, Month, Quarter, Year, Season). A secondary "Financial Summary Star" uses "FactInvoice" with measures Invoice_Amount, Amount_Paid, Days_to_Pay, and Write_Off_Amount, linked to the same DimCustomer and DimDate for consistency. "Master data tables" (DimItem, DimCustomer, DimWarehouse) are shared across stars to ensure conformed dimensions—for example, "Durham" always maps to "Historical costumes", preventing reporting discrepancies. "Aggregate tables" like "AggRental_Monthly" pre-calculate totals by warehouse and category (e.g., total revenue from Colchester's large props in January) to accelerate dashboard performance. "Metadata tables" such as "MetaETL_Log" track data lineage (source system, extraction time, rows processed, errors), while "MetaItem_History" records changes to item cost or category over time (e.g., if a prop is reclassified from "small" to "common core"). This design supports critical business questions: "What is the net profit margin on emergency rentals of common core items after fuel costs?" or "How do delivery costs impact small orders (¡£5,000) dispatched from Blackburn?" and ensures the system remains scalable, maintainable, and aligned with business terminology, as recommended by leading data warehouse methodologies [11]. The approach follows the modern dimensional design principles outlined by Golfarelli and Rizzi (2020), which prioritise business understandability and query efficiency in multi-source environments [12]. Karadimas and Loukopoulos (2022) provide a validated framework for evaluating such schemas, confirming that conformed dimensions and aggregate tables significantly improve usability and trust in enterprise settings [13].

Table 1: Structure of the `FactRental` table

Column	Description
Rental_SK	Surrogate key for the rental transaction
Item_SK	Foreign key to DimItem (e.g., “Pantomime Dame Dress”)
Customer_SK	Foreign key to DimCustomer (e.g., “Amateur Theatre Group A”)
Warehouse_SK	Foreign key to DimWarehouse (e.g., “Abergavenny”)
Date_SK	Foreign key to DimDate (rental start date)
Daily_Rate	Base rental price per day (£)
Days_Rented	Number of full rental days (integer)
Discount_Amount	Total discount applied (£)
Emergency_Surcharge	15% fee if delivery ¡14 days (£)
Delivery_Cost	Transport cost based on distance and vehicle (£)
Total_Rental_Fee	Computed: (Daily_Rate × Days_Rented) Discount + Surcharge

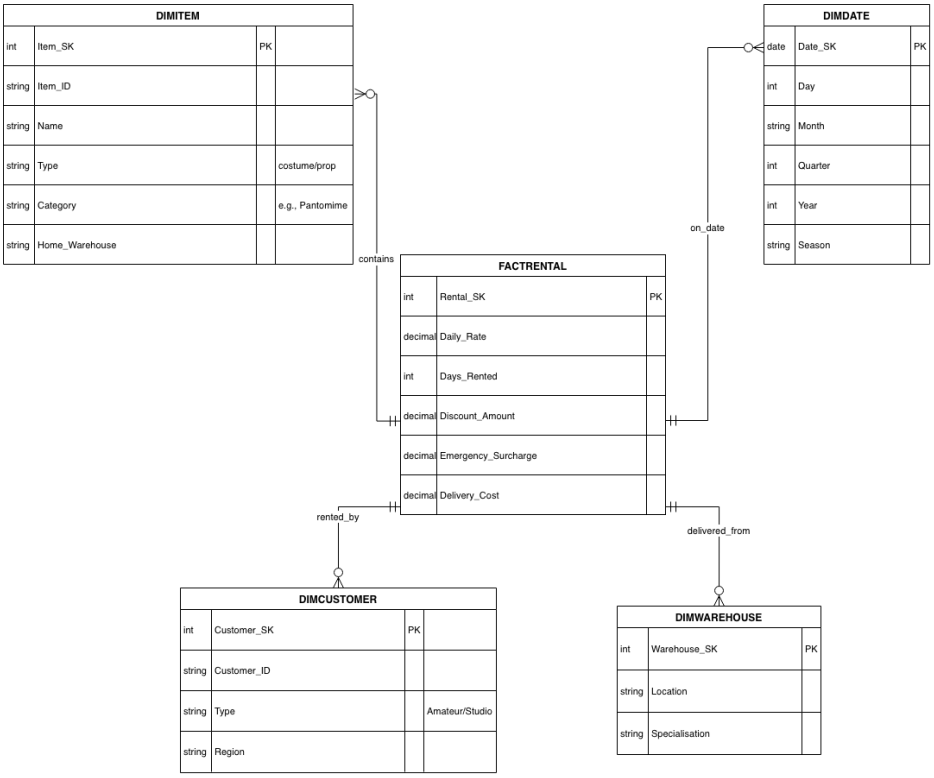

Figure 3: Star schema example showing FactRental linked to dimension tables.

2.4 Data Marts

Three data marts will be derived from the central schema to serve key departments. The ”Corporate Performance Mart” serves the Managing Director with high-level KPIs: monthly profit by warehouse (e.g., comparing seasonal spikes in Abergavenny to steady demand in Durham), inventory turnover rates (e.g., how many times Freuchie’s small props are rented annually), and ROI on new acquisitions (e.g., cost vs. rental income for a new armoured car in Colchester). The ”Finance Mart” supports the Finance Director with detailed cash flow analysis, late payment tracking (e.g., percentage of £10,000+ orders paid after the 7-day window), and net profit calculations that factor in all costs—delivery fuel, item write-offs, and emergency staffing. This mart can answer whether the 15% emergency surcharge truly covers the extra operational burden. The ”Sales and Marketing Mart” enables the

Sales Director to explore customer behaviour: Which "Room in a Box" themes (18th-century drawing room vs. space station bunk room) are most popular among film studios? Do discounts on extra military uniforms from Evesham increase total order value or just encourage larger but less profitable orders? Each mart is a logical subset of the central data, ensuring consistency while tailoring metrics to departmental workflows. This approach reduces training needs, increases user adoption, and empowers evidence-based decisions that align with strategic goals, as observed in similar implementations in service-oriented businesses [6].

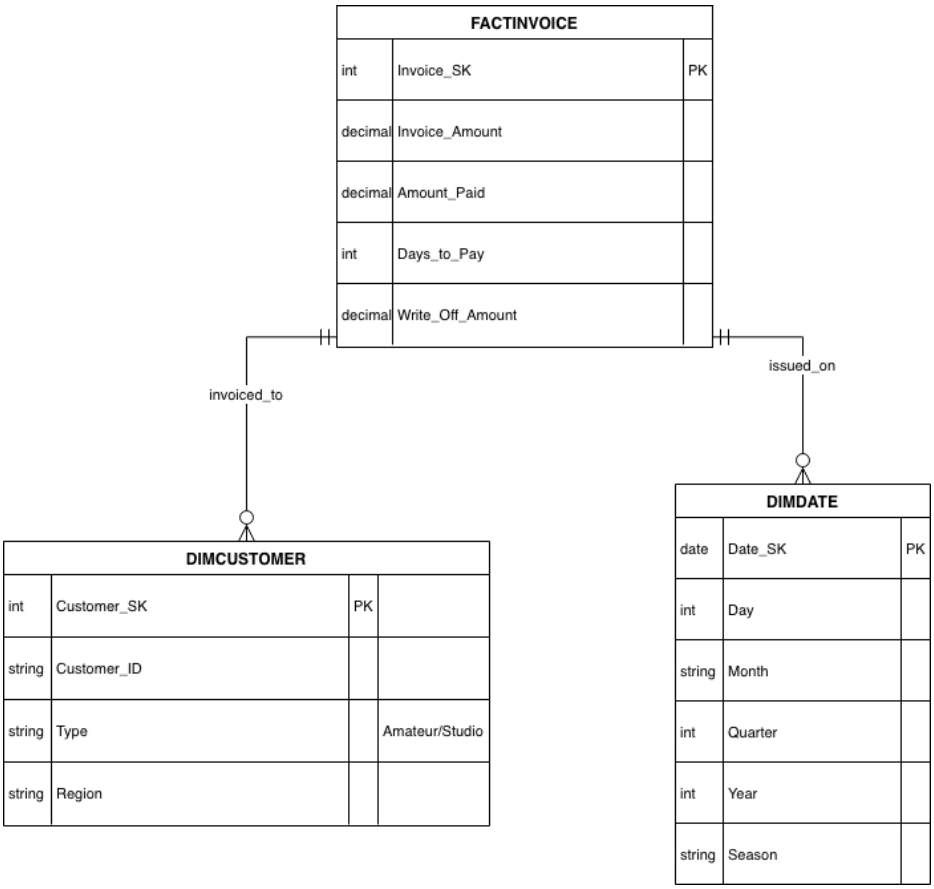

Figure 4: Finance Data Mart schema showing FactInvoice linked to DimCustomer and DimDate for tracking cash flow, late payments, and write-offs.

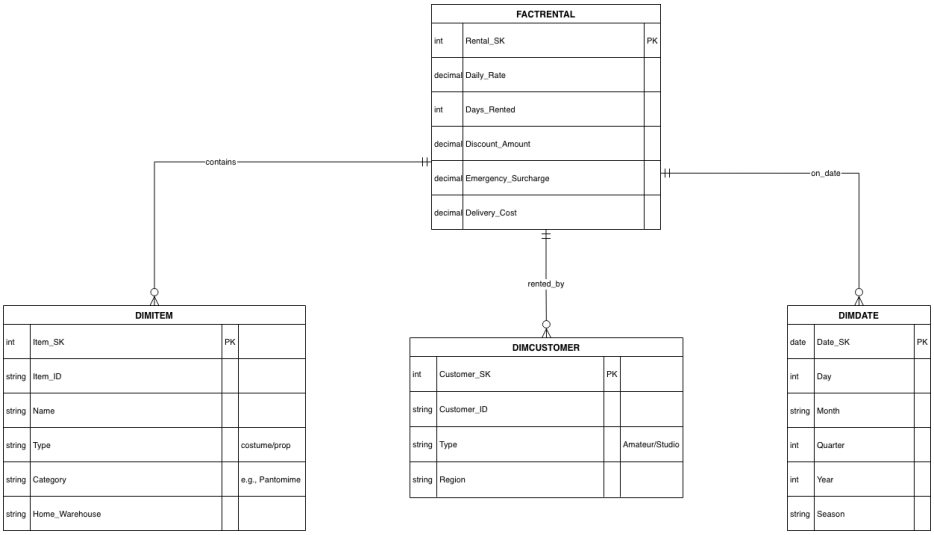

Figure 5: Sales and Marketing Data Mart schema showing FactRental linked to DimItem, DimCustomer, and DimDate for analysing item popularity, regional demand, and discount effectiveness.

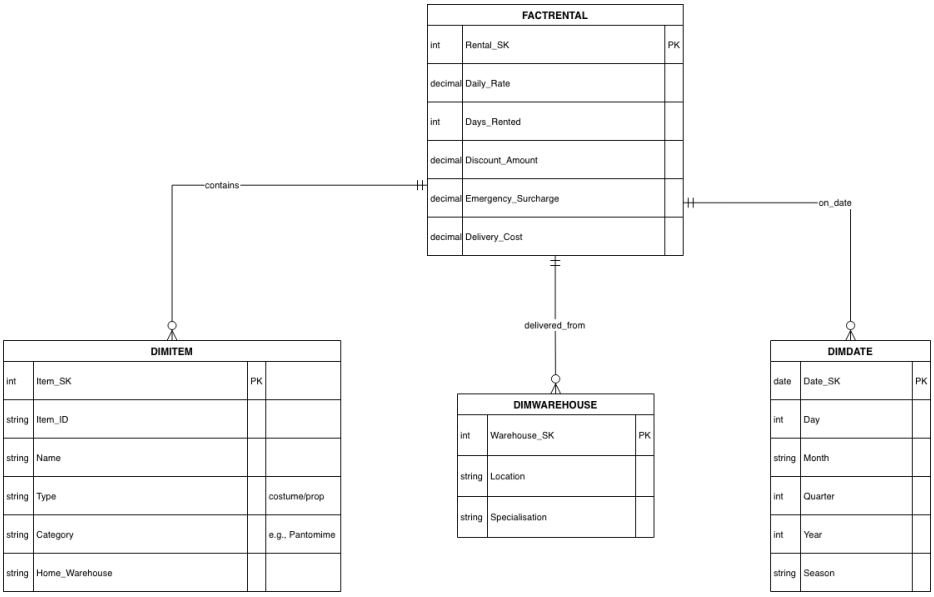

Figure 6: MD Performance Data Mart schema showing FactRental linked to DimItem, DimWarehouse, and DimDate for measuring profit by warehouse, inventory turnover, and ROI on acquisitions.

2.5 Simplified ETL Plan

The ETL process will run nightly to ensure fresh data without disrupting operations. Data is extracted via secure SQL queries from the Orders, Transport, Inventory, and Finance databases. Transformations include: standardising all date formats to ISO 8601; calculating Days_Rented as (Return_Date Delivery_Date); computing Total_Rental_Fee = (Daily_Rate × Days_Rented) Discount_Amount + Emergency_Surcharge; mapping warehouse codes (e.g., “ABG”) to full names (“Abergavenny”); flagging emergency orders where (Delivery_Date Order_Date) ¡ 14; and assigning surrogate keys using Type 2 slowly changing dimension logic to track item or customer history. Data is then loaded into the fact and dimension tables in the data warehouse. Aggregate tables like AggRental_Monthly are refreshed weekly to support dashboard performance. The entire process uses

read-only database connections and executes between 2:00 AM and 5:00 AM, ensuring zero impact on daytime activities such as order entry, delivery scheduling, or inventory checks. Error logs are generated for any failed steps and sent to the IT team for resolution, ensuring data reliability and system stability [3].

2.6 Data Quality & Governance Issues

Key data quality risks include inconsistent item categorisation across warehouses (e.g., is a ceremonial sword a "small prop" or part of a "military uniform" set?), missing delivery signatures due to connectivity issues on remote film sets, and duplicate customer entries when amateur groups re-register under slightly different names. Governance solutions include enforcing validation rules during ETL (e.g., mandatory category fields, range checks on dates), implementing master data management for customers and items to ensure unique, consistent identifiers, and maintaining comprehensive audit logs in metadata tables. GDPR compliance is essential for customer data, requiring strict role-based access controls, data anonymisation in non-production environments, and secure handling of personal information during ETL and reporting. Regular data quality assessments will be conducted by a cross-functional governance committee to ensure the warehouse remains a trusted source of truth for strategic decision-making [14]. As Mills (2021) emphasises, proactive data quality monitoring reduces downstream reporting errors by over 60 per cent, justifying investment in validation rules during ETL [15].

2.7 Conclusion

The proposed star schema and ETL plan provide Rags'n'Riches Ltd. with a robust, scalable foundation to harness data for strategic growth, operational excellence, and competitive advantage in the expanding UK film market. By transforming fragmented operational data into actionable insights, the company will be well-positioned to capitalise on new opportunities and drive sustainable profitability.

Appendices

All figures and tables were created by the author. The diagrams were generated to represent concepts and illustrate key points discussed in the text.

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