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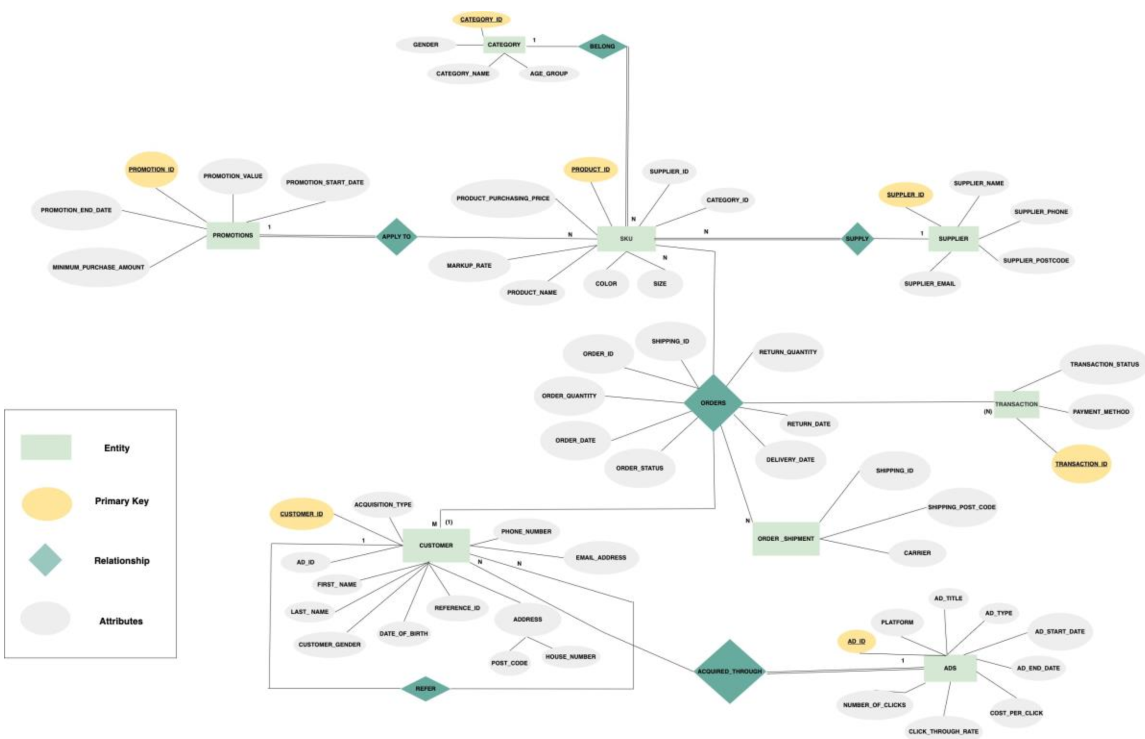
Introduction

This project undertook a comprehensive approach to data management for an apparel e-commerce retailer based in the UK, encompassing database design, data analysis, and re-porting. The database architecture was structured around eight entities including products, customers, shipments, promotions, advertisements, suppliers, categories, and transactions, depicted through an Entity-Relationship (ER) diagram. An SQL schema was then implementedto substantiate this design. R was employed to generate synthetic data aligned with our schema to simulate real-world retail transactions. Rigorous data quality assurance was con- ducted before writing the data into the database. Subsequently, Quarto with R was utilised for data analysis to offer practical insights for strategic decision-making. Automation of data validation, loading, and analysis processes was achieved through a GitHub workflow, ensuring collaborative oversight and accountability throughout the project lifecycle.

Part 1: Database Design and Implementation

1.1 : E-R Diagram Design



The E-R diagram contained eight entities and relationships, depicting the operational structure of an apparel e-commerce retailer based in the UK. It illustrated the journey of an order starting from a registered customer selecting a product (SKU), through to the order's delivery, and handling of any subsequent returns. It also covered the process of customer acquisition through three main channels, organic, advertisement and referrals. Please refer to Appendix 1 for the definition of each attribute of each entity.

We made the following assumptions:

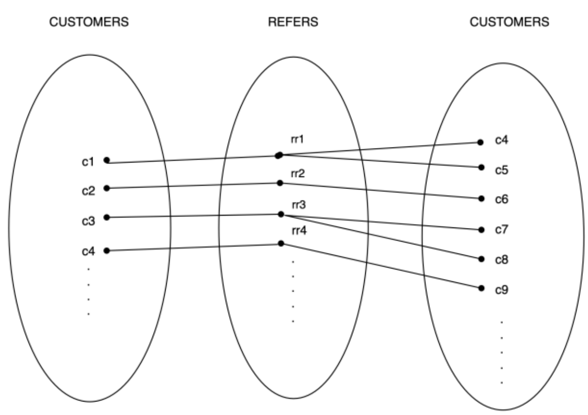
- Product is tracked at the SKU level.
- Promotion codes are applied at SKU level.
- Customers must register before placing orders.
- Third-party analytics (e.g., Apps flyer) is used for marketing and customer attribution, thus we can track paid customers are acquired from which ads.
- One order can be paid by only one transaction.
- One new customer can be referred by only one existing customer.
- Customers can only return the order within 30 days from order placement date.
- Every order will be delivered in one shipment.

Relationships Between Entities:

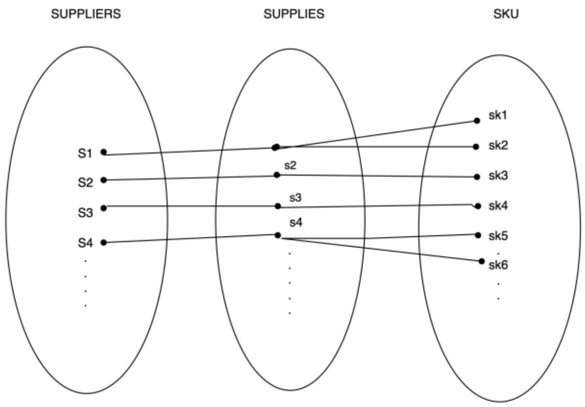
Our E-R diagram had two types of relationships between different entities, many-to-one and many-to-many.

One-to-many:

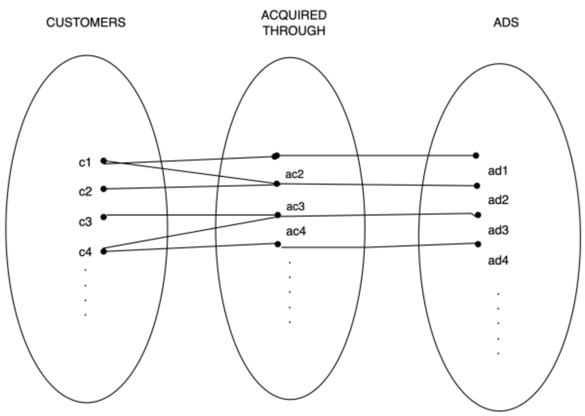
- CUSTOMERS refers CUSTOMERS: A self-recursive relationship, in which one existing customer can refer many new customer, but one new customer can only be referred by one existing customer.



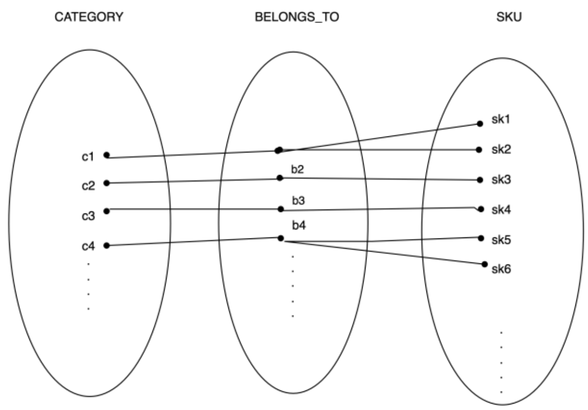
- SUPPLIERS supply SKU: One supplier can supply many products while one SKU isonly provided by only one supplier.



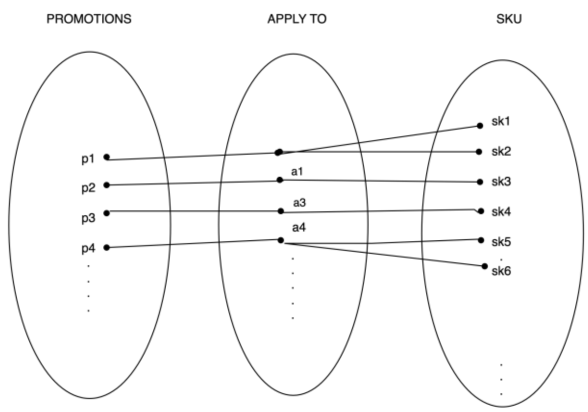
- CUSTOMERS acquired through ADS: One advertisement can be used to acquire many customers whilst one customer can only be acquired through one advertisement.



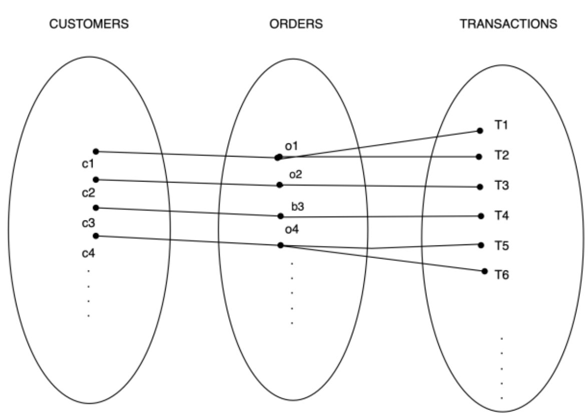
- SKU belongs to CATEGORY: Many products can belong to one category.



- PROMOTIONS apply to SKU: One promotion can be applied to many products.

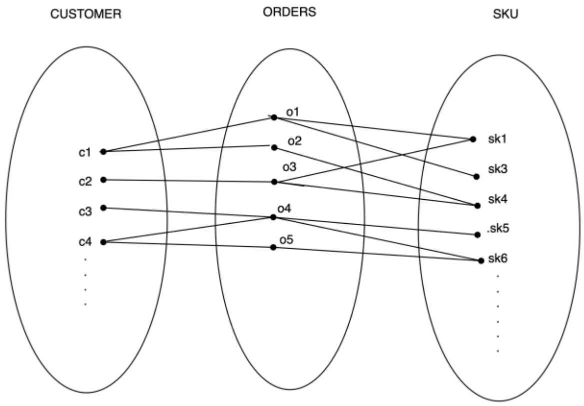


- CUSTOMERS pay TRANSACTIONS: one transaction can only be paid by one customerwhile one customer can pay multiple transactions.

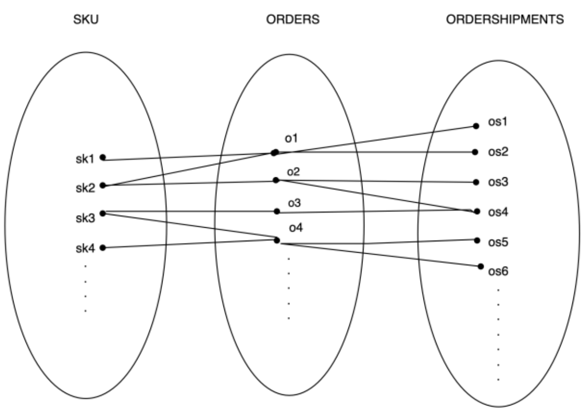


Many-to-many:

- CUSTOMERS order SKU: One customer can order many products and one product canbe ordered multiple times.



- SKU delivered through ORDER_SHIPMENT: Many products can have multiple order shipments.



1.2: SQL Database Schema Creation

In creating logical and physical schema, to satisfy 3NF normalisation, we ensured that (1) each attribute was single-value, (2) each table had its unique primary key, (3) all attributes in all tables represented distinctive information, (4) no inferred data was stored (e.g. calculated field), (5) in a table, except for the primary key, other attributes were not dependent on each other. Subsequently, considerations were made for data volume and performance requirements, selecting appropriate data types and indexes to optimise query performance. Based on these designs, the physical schema was created using the SQL, including table structures, indexes, and constraints. Notably, as ORDER is a many-to-many relationship, an ORDERS table wascreated in the logical and physical schema.

To derive the physical schema of the database, entity-relationship modeling and normalization were conducted initially. This involved identifying entities, attributes, and relationships, ensuring that the data model adhered to third normal form (3NF). Subsequently, considerations were made for data volume and performance requirements, selecting appropriate data types and indexes to optimize query performance. Finally, based on these designs, the physical schema was created using the SQL language, including table structures, indexes, and constraints.

Logical Schema

ORDERS (ORDER_ID, CUSTOMER_ID, TRANSACTION_ID, PRODUCT_ID, SHIPPING_ID, ORDER_DATE, ORDER_STATUS, DELIVERED_DATE, ORDER_QUANTITY, RETURN_QUANTITY, RETURN_DATE)

ORDER_SHIPMENT (SHIPPING_ID, POST_CODE, CARRIER)

TRANSACTION (TRANSACTION_ID, PAYMENT_METHOD, TRANSACTION_STATUS)

PROMOTION (PROMOTION_ID, PRODUCT_ID, PROMOTION_VALUE, PROMOTION_START_DATE, PROMOTION_END_DATE, MINIMUM_PURCHASE_AMOUNT)

ADS (AD_ID, PLATFORM, AD_TITLE, AD_TYPE, AD_START_DATE, AD_END_DATE, COST_PER_CLICK, CLICK_THROUGH_RATE, NUMBER_OF_CLICKS)

CUSTOMERS (CUSTOMER_ID, AD_ID, REFERENCE_ID, CUSTOMER_EMAIL, CUSTOMER_GENDER, PHONE_NUMBER, LAST_NAME, FIRST_NAME, DATA_OF_BIRTH, POST_CODE, HOUSE NUMBER, ACQUISITION_TYPE)

CATEGORY (CATEGORY_ID, CATEGORY_NAME, GENDER, AGE_GROUP)

SUPPLIER (SUPPLER_ID, SUPPLIER_NAME, SUPPLIER_PHONE, POST_CODE, SUPPLIER_EMAIL)

SKU (PRODUCT_ID, SUPPLER_ID, CATEGORY_ID, PRODUCT_NAME, PRODUCT_PURCHASING_PRICE, COLOR, SIZE, MARKUP)

Physical Schema

```
rm(list=ls())
library(readr)
library(RSQLite)
library(dplyr)

#Creating a connection to a database
my_db <- RSQLite::dbConnect(RSQLite::SQLite(),"/cloud/project/ecommerce.db")
```

- ADS

```
CREATE TABLE ADS(
  AD_ID VARCHAR(30) PRIMARY KEY,
  PLATFORM VARCHAR(255),
  AD_TITLE VARCHAR(255),
  AD_TYPE VARCHAR(70),
  AD_START_DATE VARCHAR(15),
  AD_END_DATE VARCHAR(15),
  COST_PER_CLICK FLOAT,
  CLICK_THROUGH_RATE FLOAT,
  NUMBER_OF_CLICK FLOAT
);
```

- CATEGORY

```
CREATE TABLE CATEGORY(
  CATEGORY_NAME TEXT NOT NULL,
  GENDER TEXT,
  AGE_GROUP VARCHAR(30),
  CATEGORY_ID VARCHAR(30) PRIMARY KEY
);
```

- SUPPLIER

```
CREATE TABLE SUPPLIER (
    SUPPLIER_NAME VARCHAR(50),
    SUPPLIER_EMAIL VARCHAR(30),
    SUPPLIER_PHONE NUMERIC(10),
    POST_CODE VARCHAR(30),
    SUPPLIER_ID VARCHAR(30) PRIMARY KEY
);
```

- CUSTOMERS

```
CREATE TABLE IF NOT EXISTS CUSTOMERS(
  CUSTOMER_ID VARCHAR(30) PRIMARY KEY,
  ACQUISITION_TYPE TEXT,
  REFERENCE_ID VARCHAR(30),
  PHONE_NUMBER NUMERIC(10),
  CUSTOMER_GENDER TEXT,
  DATE_OF_BIRTH VARCHAR(15),
  FIRST_NAME TEXT,
  LAST_NAME TEXT,
  CUSTOMER_EMAIL VARCHAR(30),
  POST_CODE VARCHAR(30),
  HOUSE_NUMBER INT,
  AD_ID VARCHAR(30),
  FOREIGN KEY (AD_ID) REFERENCES ADS (AD_ID)
  FOREIGN KEY (REFERENCE_ID) REFERENCES CUSTOMER(CUSTOMER_ID)
);
```

- PRODUCT

```
CREATE TABLE IF NOT EXISTS SKU(
    COLOR TEXT,
    SIZE TEXT,
    PRODUCT_NAME TEXT,
    PRODUCT_ID VARCHAR(30) PRIMARY KEY,
    PRODUCT_PURCHASING_PRICE FLOAT,
    MARKUP FLOAT,
    SUPPLIER_ID VARCHAR(30),
    CATEGORY_ID VARCHAR(30),
    FOREIGN KEY (SUPPLIER_ID) REFERENCES SUPPLIER(SUPPLIER_ID),
    FOREIGN KEY (CATEGORY_ID) REFERENCES CATEGORY(CATEGORY_ID)
);
```

- PROMOTION

```
CREATE TABLE PROMOTION (
  PROMOTION_ID VARCHAR(30) PRIMARY KEY,
  PROMOTION_VALUE FLOAT,
  PROMOTION_START_DATE VARCHAR(15),
  PROMOTION_END_DATE VARCHAR(15),
  MINIMUM_PURCHASE_AMOUNT FLOAT,
```

```
  PRODUCT_ID VARCHAR(30),
  FOREIGN KEY (PRODUCT_ID) REFERENCES SKU(PRODUCT_ID)
);
```

- TRANSACTION

```
CREATE TABLE TRANSACTIONS (
  TRANSACTION_ID VARCHAR(30) PRIMARY KEY,
  PAYMENT_METHOD VARCHAR(50),
  TRANSACTION_STATUS VARCHAR(50)
);
```

- ORDER_SHIPMENT

```
CREATE TABLE ORDER_SHIPMENT(
  SHIPPING_ID VARCHAR(30) PRIMARY KEY,
  POST_CODE VARCHAR(30),
  CARRIER TEXT
);
```

- ORDERS

```
CREATE TABLE ORDERS (
  ORDER_ID VARCHAR(30),
  CUSTOMER_ID VARCHAR(30),
  ORDER_DATE VARCHAR(15),
  ORDER_STATUS TEXT,
  SHIPPING_ID VARCHAR(30),
  DELIVERY_DATE VARCHAR(15),
  TRANSACTION_ID VARCHAR(30),
  PRODUCT_ID VARCHAR(30),
  ORDER_QUANTITY INTEGER,
  RETURN_QUANTITY INTEGER,
  RETURN_DATE VARCHAR(15),
  PRIMARY KEY (ORDER_ID, PRODUCT_ID, CUSTOMER_ID),
  FOREIGN KEY (PRODUCT_ID) REFERENCES SKU(PRODUCT_ID),
  FOREIGN KEY (CUSTOMER_ID) REFERENCES CUSTOMERS(CUSTOMER_ID),
  FOREIGN KEY (TRANSACTION_ID) REFERENCES TRANSACTIONS(TRANSACTION_ID)
  FOREIGN KEY (SHIPPING_ID) REFERENCES SHIPMENT(SHIPPING_ID)
);
```

Part 2: Data Generation and Management

2.1: Synthetic Data Generation

All synthetic data generation was conducted solely in R and saved into csv files before pushed to GitHub, ensuring adherence to attribute conditionalities and inter-entity connections with the support of LLM. Initially, Mockaroo was explored for data generation, but its high level of randomisation proved more complex compared to R for setting precise rules to control data values (see Figure 1).

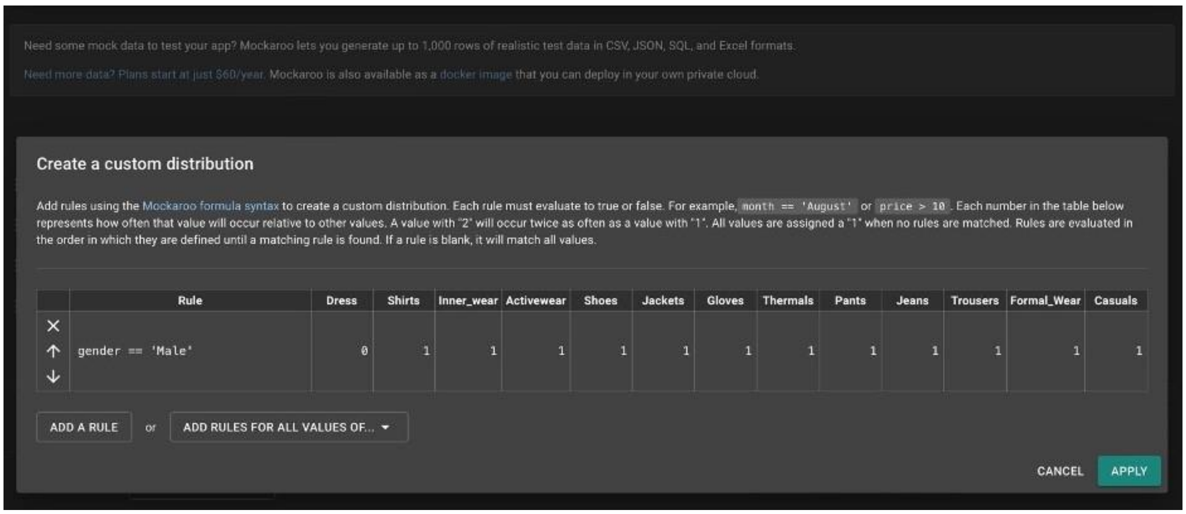


Figure 1 - Customising data values in Mockaroo

In R, independent entities such as CATEGORY, SUPPLIER, PROMOTION, ADS, SKU and CUSTOMERS were created first. We asked LLM to generate values for CATEGORY_NAME, PRODUCT_NAME, SUPPLIER_NAME, AD_TITLE, tailored to the fashion retail industry (Figure 2 and 3). The generation of SUPPLIER_EMAIL and CUSTOMER_EMAIL utlised a function suggested by LLM (Figure 4). Postal codes were randomly generated from UK post- codes using “PostcodesioR” package drawing on data from Office for National Statistic (Walczak, E., 2021). Customer names were randomly created employing “randomNames” package (Betebenner, D.W., 2021). All numerical fields such PRODUCT_PURCHASING_PRICE, MARKUP, etc. were randomised using either “runif” or “sample” functions to ensure realis- tic value distributions. Furthermore, for CUSTOMERS, REFERENCE_ID, denoting CUS- TOMER_ID of the referees, was conditioned such that the referred customers were only included in our database after their referees. REFERENCE_ID was exclusively limited to customers with an ACQUISITION_TYPE of “Referral” while AD_ID was randomly assigned from ADS table for customers with an ACQUISITION_TYPE of “Paid”.

Please refer to Appendix A2 for the full prompt sequences in LLM.

```
# Create name
##    Filter    out    names    with    apostrophes
filtered_names                                          <-
randomNames(nrow(CUSTOMER))
filtered_names <- filtered_names[!grepl("'", filtered_names)]

## If the number of filtered names is less than
## the number of rows in CUSTOMER, generate additional namesif
(length(filtered_names) < nrow(CUSTOMER)) {
   additional_names <- randomNames(nrow(CUSTOMER) - length(filtered_names))
   additional_names      <-      additional_names[!grepl("'",      additional_names)]
   filtered_names <- c(filtered_names, additional_names)
}

## Generate random full names
random_full_names <- sample(filtered_names, nrow(CUSTOMER), replace = TRUE)

#W  Split  full  names  into  first  and  last  names
split_names <- strsplit(random_full_names, ",")

## Extract first names
CUSTOMER$FIRST_NAME <- sapply(split_names, "[", 2)

## Extract last names
CUSTOMER$LAST_NAME <- sapply(split_names, "[", 1)

#                         CREATE
CUSTOMER_POST_CODE
CUSTOMER$POST_CODE
<-
sapply(1:nrow(CUSTOMER),                    function(x)                  random_postcode()$postcod
```

Figure 4 - LLM prompt for email generation

Subsequently, dependent tables including ORDERS, ORDER_SHIPMENT and TRANSACTIONS were created based on the data from the previous tables. Specifically, in ORDERS, combinations of CUSTOMER_ID and PRODUCT_ID were randomly selected from SKU and CUSTOMERS tables so that a customer can purchase multiple products in an order. The generation of DELIVERY_DATE and RETURN_DATE adhered to constraints derived from OR- DER_DATE, ensuring that DELIVERY_DATE fell within a maximum of 7 days after order placement, and RETURN_DATE occurred after DELIVERY_DATE while remaining within 30 days from ORDER_DATE. ORDER_STATUS was randomised to reflect an authentic distribution encompassing “Returned”, “Delivered” and “In transit”. RETURN_QUANTITY and RETURN_DATE was exclusively assigned to orders marked as “Returned”, with RE- TURN_QUANTITY restricted not to exceed ORDER_QUANTITY. Moreover, for TRANS- ACTIONS table, we also ensured that all orders have matching successful transactions, with the proportion of failed transaction set to 6% of total transaction numbers.

.

```
# Create ORDER dataframe
ORDER <- data.frame(ORDER_ID = paste0("OD", seq_len(1000) + 10000),
   stringsAsFactors = TRUE
)

# Add CUSTOMER_ID
ORDER$CUSTOMER_ID <- sample(CUSTOMER$CUSTOMER_ID,nrow(ORDER),replace=TRUE)


#                    Add
ORDER_DATE
ORDER$ORDER_D
ATE <-
sample(seq(start_date, end_date, by = "day"), nrow(ORDER), replace = TRUE)

# Add ORDER_STATUS:
order_status  <-  c("Delivered",  "Returned")  proportions  <-
c("Delivered" = 0.8, "Returned" = 0.2)

#     Sample     proportionally     with     replacement     and     assign     to
ORDER$ORDER_STATUSORDER$ORDER_STATUS <-
sample(order_status,  size  =  nrow(ORDER),  replace  =  TRUE,  prob  =  proportions)
ORDER$ORDER_STATUS[ORDER$ORDER_DATE>'2024-03-05'] = "In transit"

# Add SHIPPING_ID
ORDER$SHIPPING_ID                              <-

ORDER_SHIPMENT$SHIPPING_ID      #      Add

DELIVERY_DATE

ORDER$DELIVERY_DATE <- ORDER$ORDER_DATE + sample(7,nrow(ORDER),replace=TRUE)
ORDER$DELIVERY_DATE[ORDER$ORDER_STATUS  %in%  c("Order  placed",  "In  transit")]  <-
NULL

#                          Add
TRANSACTION_ID
ORDER$TRANSACTION
_ID <-
TRANSACTION$TRANSACTION_ID[TRANSACTION$TRANSACTION_STATUS == "Successful"]

# Create an empty dataframe to store order-product mappings
order_product_mapping <-
data.frame(ORDER_ID = character(), PRODUCT_ID = character(), stringsAsFactors = FALSE)
```

```
# Define the number of products per order
products_per_order <- round(runif(nrow(ORDER), min = 1, max = 10))

# Loop through each order ID and sample productsfor
(i in 1:nrow(ORDER)) {
   order_id                              <-
   ORDER$ORDER_ID[i]
   product_ids <-
   sample(SKU$PRODUCT_ID, size = products_per_order[i], replace = FALSE)
   order_product_mapping <- rbind(order_product_mapping,
   data.frame(ORDER_ID = rep(order_id, length(product_ids)), PRODUCT_ID = product_ids))
}

# Merge order_product_mapping with ORDER dataframe to retain other order details
ORDER <- merge(ORDER, order_product_mapping, by = "ORDER_ID", all.x = TRUE)

# Add ORDER_QUANTITY
ORDER$ORDER_QUANTITY    <-round(runif(nrow(ORDER),min=1,max=5),0)

#                            Add
RETURN_QUANTITY
ORDER$RETURN_QUAN
TITY <-
ifelse(ORDER$ORDER_STATUS=="Returned",
mapply(function(x) sample(1:x, 1), ORDER$ORDER_QUANTITY),"")

# Add RETURN_DATE
ORDER$RETURN_DATE              <-              ORDER$ORDER_DATE              +
sample(9:30,nrow(ORDER),replace=TRUE)
ORDER$RETURN_DATE[ORDER$ORDER_STATUS != "Returned"] <- ""

# Change DATE to CHARACTER
ORDER$ORDER_DATE                                    <-
as.character(ORDER$ORDER_DATE)
ORDER$RETURN_DATE                                   <-
as.character(ORDER$RETURN_DATE)
ORDER$DELIVERY_DATE                                 <-
as.character(ORDER$DELIVERY_DATE)

#Save          to          csv
write.csv(ORDER[1:15,],
file   =   file.path("/cloud/project/Data","ORDERS.1.csv"),   row.names   =   FALSE)
write.csv(ORDER[16:nrow(ORDER),],
file = file.path("/cloud/project/Data","ORDERS.2.csv"), row.names = FALSE)
```

2.2: Data Import and Quality Assurance

An R script was developed to load all data files in their respective corresponding tables within our database, ensuring robust data quality and integrity. This process involved connecting tothe database and iteratively validating data entries against predefined criteria.

The script employed a loop cross-checking primary key values to prevent duplications and enforcing strict validation rules on a row by row basis. Entries were scrutinised for null values, adherence to formatting standards for phone numbers and emails, and non-negativity in numeric fields. For formatting check, we defined functions to automatically validate. Data entries satisfying these validation criteria were then appended to the database whilst problematic entries were recorded in “error_log.txt” file for further reviews.

```
library(readr)
library(RSQLite)
library(dplyr)
library(DBI)

# Define a function to check if phone numbers are of length 10# and
contain only numeric characters
validate_phone_numbers <- function(phone) {
  phone <- as.character(phone)   # Convert integer to character
  if (!is.na(phone) && nchar(phone) == 10 && !any(is.na(as.numeric(phone)))) {
    return(TRUE)   # Phone number is valid
  } else {
    return(FALSE) # Phone number is not valid
  }
}



# Function to validate email addresses
email_pattern <- "^[a-zA-Z0-9._%+-]+@[a-zA-Z0-9.-]+\\.[a-zA-Z]{2,}$"
validate_emails <- function(email) {
  grepl(email_pattern, email)
}

# Function to validate that numeric attributes are non-negative
check_non_negative_numeric <- function(data) {
  numeric_cols <- sapply(data, is.numeric)
  negative_values <- sapply(data[numeric_cols], function(col) any(col < 0))
  return(!any(negative_values))
}
```

```
# Establishing the connection to db
my_db <- RSQLite::dbConnect(RSQLite::SQLite(), "ecommerce.db")

file_paths <- list(
  "ADS" = list.files(path = "Data", pattern = "ADS.*\\.csv$", full.names = TRUE),
  "CATEGORY" = list.files(path = "Data",
  pattern = "CATEGORY.*\\.csv$", full.names = TRUE),
  "SUPPLIER" = list.files(path = "Data",
  pattern = "SUPPLIER.*\\.csv$", full.names = TRUE),
  "CUSTOMERS" = list.files(path = "Data",
  pattern = "CUSTOMERS.*\\.csv$", full.names = TRUE),
  "SKU" = list.files(path = "Data",
  pattern = "SKU.*\\.csv$", full.names = TRUE),
  "PROMOTION" = list.files(path = "Data",
  pattern = "PROMOTION.*\\.csv$", full.names = TRUE),
  "TRANSACTIONS" = list.files(path = "Data",
  pattern = "TRANSACTIONS.*\\.csv$", full.names = TRUE),
  "ORDER_SHIPMENT" = list.files(path = "Data",
  pattern = "ORDER_SHIPMENT.*\\.csv$", full.names = TRUE),
  "ORDERS" = list.files(path = "Data",
  pattern = "ORDERS.*\\.csv$", full.names = TRUE)
)

tables <- list( "ADS"
  = "AD_ID",
  "CATEGORY" =
  "CATEGORY_ID", "SUPPLIER"
  = "SUPPLIER_ID",
  "CUSTOMERS" =
  "CUSTOMER_ID", "SKU" =
  "PRODUCT_ID",
  "PROMOTION" =
  "PROMOTION_ID",
  "TRANSACTIONS" =
  "TRANSACTION_ID",
  "ORDER_SHIPMENT" =
  "SHIPPING_ID",
  "ORDERS" = c("ORDER_ID", "PRODUCT_ID", "CUSTOMER_ID")
)

# Define write_errors function with folder path argument
write_errors <- function(errors, folder_path, file_name) {
  # Ensure the folder exists, if not, create it if
  (!dir.exists(folder_path)) {
    dir.create(folder_path, recursive = TRUE)
  }
```

```
    file_path <- file.path(folder_path, file_name)

    if (length(errors) > 0) { cat("Errors:\n",
        file = file_path)for (error in errors) {
            cat(error, "\n", file = file_path, append = TRUE)
        }
        cat("\n", file = file_path, append = TRUE)
    }
}


# List to store errors
error_list <- c()

# Function to check if data entries exist and load new entries for
(table_name in names(tables)) {
    for (file_path in file_paths[[table_name]]) {
        table_data <- read_csv(file_path,n_max = Inf)

        ## Apply specific rules for attributes based on the table if
        (table_name == "ADS") {
            # Initialize error list error_list <-
            vector("list")

            # Convert AD_START_DATE and AD_END_DATE to character
            table_data$AD_START_DATE <-
            as.character(table_data$AD_START_DATE) table_data$AD_END_DATE
            <- as.character(table_data$AD_END_DATE)

            # Initialize vector to store indices of invalid rows
            invalid_rows <- vector("numeric")

            # Ensure numeric attributes are non-negative
            numeric_attrs <- c("COST_PER_CLICK",
            "CLICK_THROUGH_RATE",
            "NUMBER_OF_CLICK")
            for (attr in numeric_attrs) {
                if (any(table_data[[attr]] < 0)) { error_list <-
                    c(error_list, paste("Negative values found
                    in", attr,"column of ADS table."))
                    invalid_rows <- c(invalid_rows, which(table_data[[attr]] < 0))
                }
            }
```

```
    # Remove invalid rows from table_data if
    (length(invalid_rows) > 0) {
      table_data <- table_data[-invalid_rows, ]
    }
  }
  if (table_name == "CUSTOMERS")
    {# Initialize error list error_list <-
    vector("list")

    # Convert DATE_OF_BIRTH to character
    table_data$DATE_OF_BIRTH <- as.character(table_data$DATE_OF_BIRTH)

    # Initialize vector to store indices of invalid rows
    invalid_rows <- vector("numeric")

    # Check phone numbers and emails
    for (i in 1:nrow(table_data)) {
      if (!validate_phone_numbers(table_data$PHONE_NUMBER[i])) {
        error_list <-
        c(error_list,
        paste("Invalid phone number in CUSTOMERS table:",
        table_data$PHONE_NUMBER[i]))invalid_rows <- c(invalid_rows, i)
      }

      if (!validate_emails(table_data$CUSTOMER_EMAIL[i])) {
        error_list <- c(error_list,
        paste("Invalid email in CUSTOMERS table:", table_data$CUSTOMER_EMAIL[i]))
        invalid_rows <- c(invalid_rows, i)
      }
    }


    # Remove invalid rows from table_data if
    (length(invalid_rows) > 0) {
      table_data <- table_data[-invalid_rows, ]
    }
  }
  if (table_name == "SKU") {#
    Initialize error list
    error_list <- vector("list")

    # Ensure numeric attributes are non-negative numeric_attrs <-
    c("MARKUP", "PRODUCT_PURCHASING_PRICE")
```

```
    for (attr in numeric_attrs) {
      if (any(table_data[[attr]] < 0)) {
        error_list <- c(error_list,
        paste("Negative values found in", attr, "column of SKU table."))
        invalid_rows <- c(invalid_rows, which(table_data[[attr]] < 0))
      }
    }


    # Remove invalid rows from table_data if
    (length(invalid_rows) > 0) {
      table_data <- table_data[-invalid_rows, ]
    }
  }
  if (table_name == "PROMOTION") {
    # Initialize error list error_list <-
    vector("list")

    # Convert PROMOTION_START_DATE and PROMOTION_END_DATE to character
    table_data$PROMOTION_START_DATE <-
    as.character(table_data$PROMOTION_START_DATE)
    table_data$PROMOTION_END_DATE <-
    as.character(table_data$PROMOTION_END_DATE)

    # Initialize vector to store indices of invalid rows
    invalid_rows <- vector("numeric")

    # Ensure numeric attributes are non-negative
    numeric_attrs <-
    c("MINIMUM_PURCHASE_AMOUNT") for (attr in
    numeric_attrs) {
      if (any(table_data[[attr]] < 0)) {
        error_list <- c(error_list,
        paste("Negative values found in", attr, "column of PROMOTION table."))
        invalid_rows <- c(invalid_rows, which(table_data[[attr]] < 0))
      }
    }


    # Remove invalid rows from table_data if
    (length(invalid_rows) > 0) {
      table_data <- table_data[-invalid_rows, ]
    }
  }
  if (table_name == "SUPPLIER") {#
    Initialize error list error_list <-
    vector("list")
```

```
    # Initialize vector to store indices of invalid rows
    invalid_rows <- vector("numeric")

    # Check phone numbers and emails
    for (i in 1:nrow(table_data)) {
      if (!validate_phone_numbers(table_data$SUPPLIER_PHONE[i])) {
        error_list <- c(error_list,
        paste("Invalid phone number in SUPPLIER table:", table_data$SUPPLIER_PHONE[i]))
        invalid_rows <- c(invalid_rows, i)
      }

      if (!validate_emails(table_data$SUPPLIER_EMAIL[i])) {
        error_list <- c(error_list,
        paste("Invalid email in SUPPLIER table:",
        table_data$SUPPLIER_EMAIL[i]))
        invalid_rows <- c(invalid_rows, i)
      }
    }


    # Remove invalid rows from table_data if
    (length(invalid_rows) > 0) {
      table_data <- table_data[-invalid_rows, ]
    }
  }
  if (table_name == "ORDERS") {#
    Initialize error list error_list <-
    vector("list")

    # Convert ORDER_DATE, DELIVERY_DATE, RETURN_DATE to
    character table_data$ORDER_DATE <-
    as.character(table_data$ORDER_DATE) table_data$DELIVERY_DATE
    <- as.character(table_data$DELIVERY_DATE)
    table_data$RETURN_DATE <-
    as.character(table_data$RETURN_DATE)

    # Initialize vector to store indices of invalid rows
    invalid_rows <- vector("numeric")
                                                                        table."))
    # Check numeric attributes for non-negativity numeric_attrs <-
    c("ORDER_QUANTITY", "RETURN_QUANTITY") for (attr in
    numeric_attrs) {
      if (any(!is.na(table_data[[attr]]) & table_data[[attr]] < 0)) { error_list <-
        c(error_list,
        paste("Invalid or negative values found in", attr, "column of ORDERS
```

```
        invalid_rows <- c(invalid_rows, which(!is.na(table_data[[attr]]) &
        table_data[[attr]] < 0))
      }
    }

    # Remove invalid rows from table_data if
    (length(invalid_rows) > 0) {
      table_data <- table_data[-invalid_rows, ]
    }
  }

  ## Check for primary key duplication for
  (i in seq(nrow(table_data))) {
    new_record      <-      table_data[i,      ]
    pk_columns    <-    tables[[table_name]]
    pk_values <- new_record[pk_columns]
    # Check if primary key values are non-null if
    (any(is.na(pk_values))) {
      error_list <- c(error_list,
      paste("Null primary key value found in", table_name, "table.")) next   #
      Skip to the next record if primary key is null
    }

    conditions <- paste(pk_columns, "=", paste0("'", pk_values, "'"),collapse =
    " AND ")

    key_exists <- dbGetQuery(my_db,
    paste("SELECT COUNT(*) FROM", table_name, "WHERE", conditions))

    if  (key_exists  ==  0)  {
      tryCatch({
        RSQLite::dbAppendTable(my_db, table_name, new_record)
      }, error = function(e) { error_list
        <- c(error_list,
        paste("Error inserting record with primary key", paste(pk_values,
        collapse = ", "), "into table", table_name)) print(paste("Error inserting
        record with primary key", paste(pk_values, collapse = ", "), "into
        table", table_name))print(e)
      })
    } else {
      print(paste("Record with primary key",
```

```
        paste(pk_values, collapse = ", "),
        "already exists in table", table_name))
      }
    }
  }
}

# Save errors to a folder named "Error logs" within the current directory
write_errors(error_list, "Error logs", "error_log.txt")
```

Part 3: Data Pipeline Generation

3.1: GitHub Repository and Workflow Setup

We initiated our project by creating a new Git repository, connecting Posit Cloud/ RStudio to the repository and uploading essential files, including (1) database, (2) data schema, (3) synthetic data generation, (4) data validation and database writing, (5) data query and analysis scripts. This setup allows us to efficiently track changes and revert to previous versions as needed.

3.2: GitHub Actions for Continuous Integration

To automate our project's operations, we implemented a GitHub Actions workflow, detailed through the following key components:

- Trigger: Activated by either a push event to the main branch or a scheduled run every 24 hours, ensuring real-time integration of contributions.
- Runner: Utilise the most recent Ubuntu environment to execute the job.
- Steps: Comprising eight sequential tasks, each step executes a specific operation withinthe job:
- Repository Checkout: Clone the project's code into the runner, providing a foundation for subsequent tasks.
- R Environment Setup: Prepare the R environment, ensuring all R-based operations canbe performed without hitches.
- R Package Caching: Preserve installed R packages between runs, significantly reducingsetup time by bypassing redundant installations.
- Package Installation: Engage only if the cache does not contain the necessary packages,ensuring all dependencies are available for the script execution.
- Script Execution: Run our R scripts from the repository to validate and load satisfying data entries to the database, subsequently creating analyses.
- Add Changes: Scans the project's database for any changes following the script's execution and notifies with a "Changes found" message if updates are identified. Meanwhile,new analyses are automatically generated and saved to folder "figures".
- Commit Changes: If changes are detected, this step prepares and commits the updatedfiles, maintaining a current state within the repository.
- Push Updates: Conclude the workflow by uploading the latest commit to the repository, ensuring all changes are synchronised and stored.

```
name: ETL workflow

on:
  push:
    branches:  [  main  ]
  schedule:
    - cron: '0 */24 * * *' # Runs every 24 hours

jobs:
  build:
    runs-on:    ubuntu-latest
    steps:
      – name: Checkout code
        uses: actions/checkout@v2

      – name:   Setup   R   environment
        uses:      r-lib/actions/setup-r@v2
        with:
          r-version: '4.2.0'

      – name:       Cache       R
        packages              uses:
        actions/cache@v2with:
          path: ${{ env.R_LIBS_USER }}
          key: ${{ runner.os }}-r-${{ hashFiles('**/lockfile') }}restore-keys:
          |
            ${{ runner.os }}-r-

      – name:   Create   figures   directory
        run: mkdir -p figures

      – name: Install packages
        if: steps.cache.outputs.cache-hit != 'true'run: |
          Rscript -e 'install.packages(c("ggplot2", "dplyr", "readr", "RSQLite", "DBI"))'

      – name:  Execute  R  script
        run: |
          Rscript R_codes/Workflow.R

      – name:  Execute  Data  Analysis
        run: |
```

```
        Rscript R_codes/Query_workflow.R
    – name:   Add   database   changes   and
      commitrun: |
        git config --global user.email "Teng-Yi.Chen@warwick.ac.uk" git
        config --global user.name "DylanCTY"
        git   add   ecommerce.db
        git add --all figures/
        git commit -m "Update database" || echo "No changes to commit" #
        Check if error logs exist
        if [ -d "Error logs" ] && [ "$(ls -A Error\ logs)" ]; then echo "Error
          logs exist"
          #   Create   error   logs   folder
          mkdir -p "Error logs"
          # Write error_log.txt
          echo "Errors:" > "Error logs/error_log.txt"
          #  Append  each  error  to  the  error_log.txt  file for
          error in Error\ logs/*; do
            cat "$error" >> "Error logs/error_log.txt"
            echo "" >> "Error logs/error_log.txt"   # Add a newline after each errordone
          # Commit error logs
          git add "Error logs/error_log.txt"
          git commit -m "Add error log" || echo "No error log changes to commit"else
          echo "No error logs found"
        fi

    – name: Push changes
      uses:    ad-m/github-push-action@v0.6.0
      with:
        github_token:  ${{  secrets.GITHUB_TOKEN  }}
        branch: main
```

Part 4: Advanced Data Analysis

Once the database was updated with the newly generated data via GitHub automation, the data was analysed utilising the R package packages dplyr, GGplot2, and tidyr in conjunction with the SQL DQL command. The procedure entailed retrieving the data and converting it into a format suitable for subsequent analysis. The complete procedure is outlined below.

Data Query

The data from the database was obtained using a SQL Data Query Language (DQL) statement. By utilising the calculated function and aggregate command, the data were converted into a format and value suitable for analysis. The following example is a query that displays the top revenue earned by product SKUs in the last 1 year, calculated by multiplying unit sales with the selling price.

```
Revenue_analysis_df <- RSQLite::dbGetQuery(my_db,
"SELECT T1.PRODUCT_ID AS PRODUCT_ID,
       T2.PRODUCT_NAME            AS
       PRODUCT_NAME,   T2.SIZE    AS
       SIZE,
       T2.COLOR    AS    COLOR,
       T1.UNIT_SOLD             AS
       UNIT_SOLD,
       T2.SELLING_PRICE_PER_UNIT AS SELLING_PRICE,
       T1.UNIT_SOLD * T2.SELLING_PRICE_PER_UNIT AS TOTAL_REVENUE
FROM
(   SELECT    ORDERS.PRODUCT_ID    AS
         PRODUCT_ID,
         ORDERS.ORDER_DATE          AS
         ORDER_DATE,
       SUM(ORDERS.ORDER_QUANTITY)    AS
UNIT_SOLDFROM ORDERS
WHERE cast(julianday('now') - julianday(ORDERS.ORDER_DATE) AS INTEGER ) <=
365GROUP BY ORDERS.PRODUCT_ID

)  AS  T1

LEFT

JOIN

(     SELECT      SKU.PRODUCT_ID      AS
         PRODUCT_ID,
         SKU.PRODUCT_NAME            AS
         PRODUCT_NAME,  SKU.SIZE   AS
         SIZE,
         SKU.COLOR                 AS                COLOR,
      SKU.PRODUCT_PURCHASING_PRICE    *    (1    +
```

```
        SKU.MARKUP) ASSELLING_PRICE_PER_UNIT
FROM SKU
) AS T2
```

```
ON T1.PRODUCT_ID = T2.PRODUCT_ID"
)
```

Data Manipulation

Once the data was imported into a R data frame, data manipulation was carried out using R to prepare the data for visualisation. The following code example generates a new columncontaining the Product SKU description.

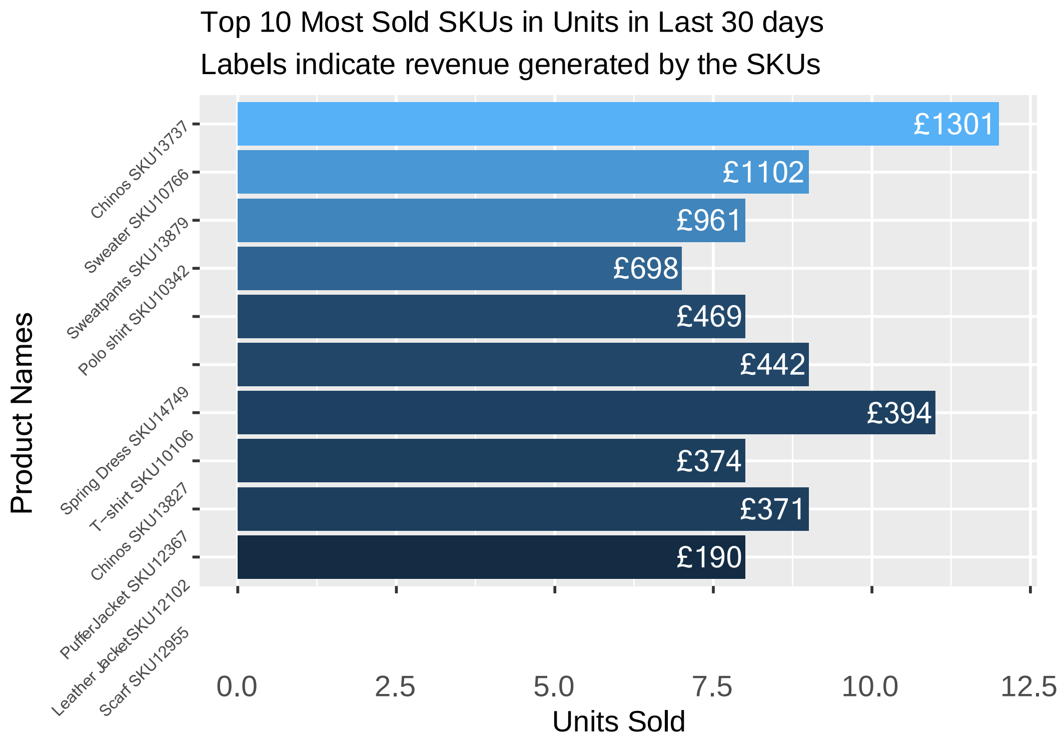
```
# Create product description name of each product_ID for using in analysis
Revenue_analysis_df$PRODUCT_DESCRIPTION <- paste(Revenue_analysis_df$PRODUCT_ID,
Revenue_analysis_df$PRODUCT_NAME, Revenue_analysis_df$SIZE,
Revenue_analysis_df$COLOR, sep = " ")
```

Data Visualisation

Finally, once we retrieved and formatted the data for analysis, we used the ggplot2 package to create visual representations of the data. The code snippet shown below demonstrates a bar chart that visually represents the top SKUs with the highest sales in the past year, as obtained from the preceding phases of our query.

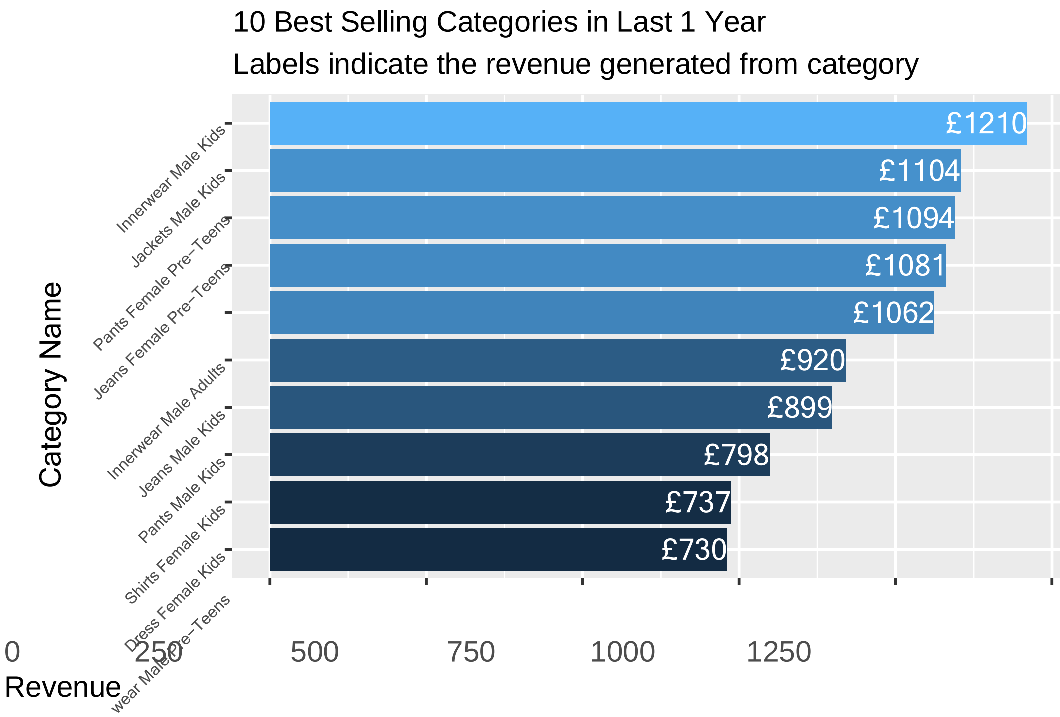
```
ggplot(data= Revenue_analysis_df %>% slice_max(TOTAL_REVENUE, n = 10)  ,
       aes(x = TOTAL_REVENUE,
       y = reorder( PRODUCT_DESCRIPTION, TOTAL_REVENUE ))) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.75),
  aes(fill=TOTAL_REVENUE), show.legend = FALSE) +
  labs(x = "Revenue", y = "Product ID and Description",
  title = "10 Best Selling Products in Last 1 Year ",
  subtitle = "Labels indicate the revenue in GBP
  generating from each product") +
  geom_text(aes(label = paste("£", round(TOTAL_REVENUE),
  sep="")), color='white', hjust = 1) +
  theme(axis.text.x = element_text(hjust = 1))
```

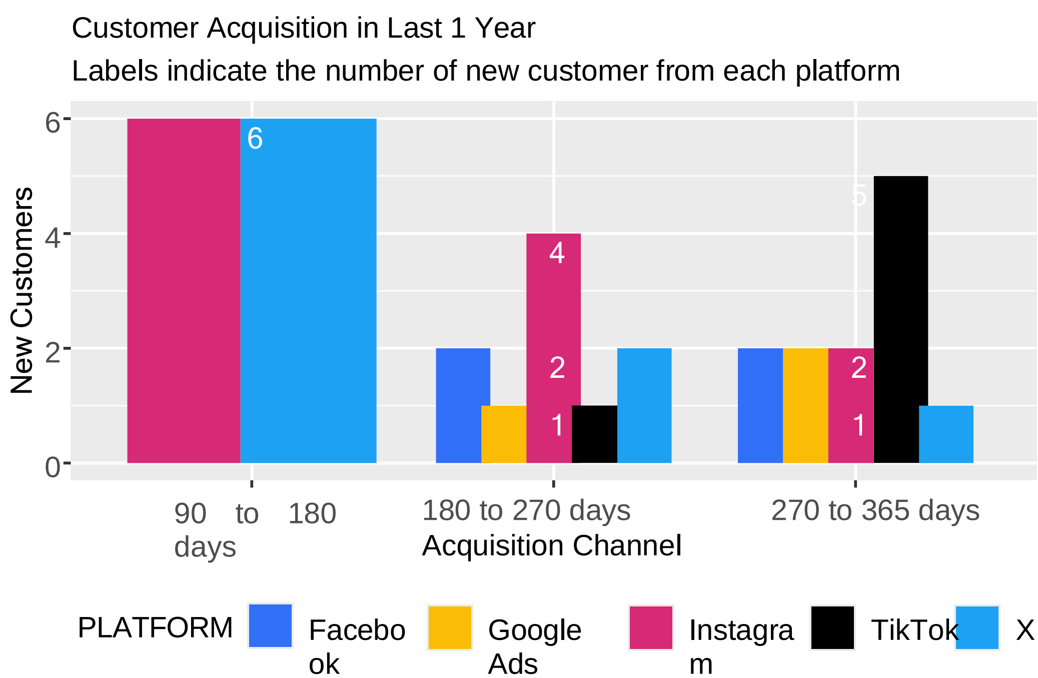
To present the data analysis, we use the R Quarto report, which can be easily changed to reflect the latest dataset. The analyses show short-term analysis for monitoring current performance in the last thirty days and long-term analysis, where we analyse changes on a yearly basis to demonstrate long-term progress.

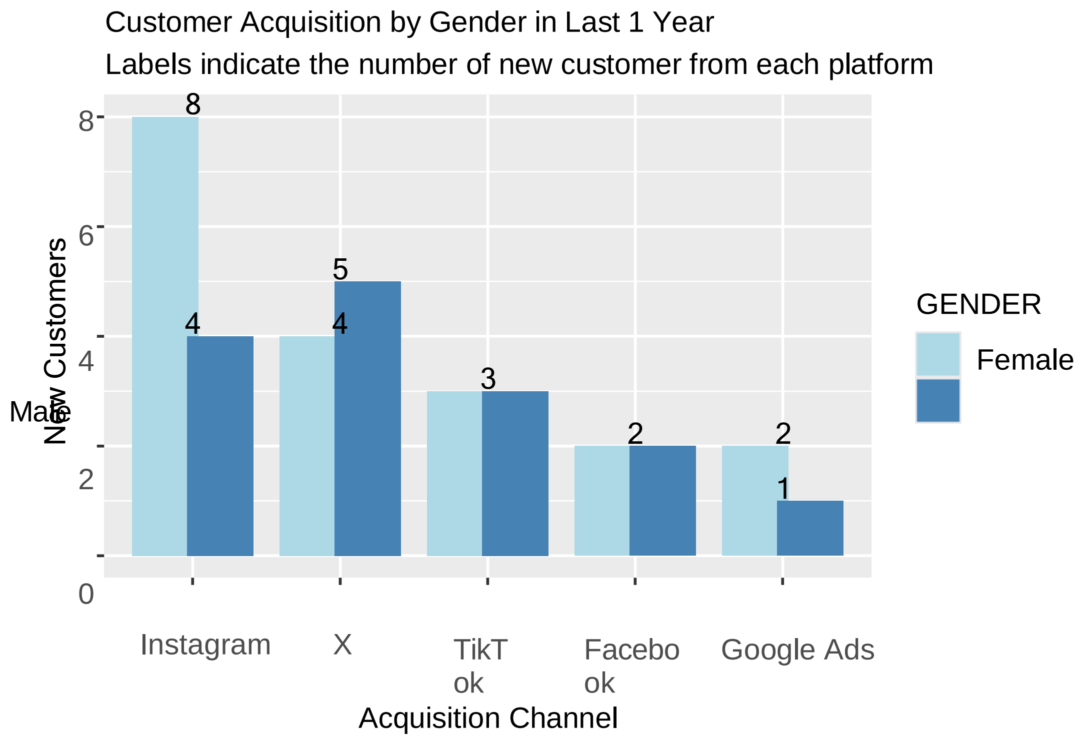


Top 10 Most Sold SKUs in Units in Last 30 days
Labels indicate revenue generated by the SKUs
Product Names
Chinos SKU13737
Sweater SKU10766
Sweatpants SKU13879
Polo shirt SKU10342
Spring Dress SKU14749
T−shirt SKU10106
Chinos SKU13827
PufferJacket SKU12367
Leather JacketSKU12102
Scarf SKU12955
£1301
£1102
£961
£698
£469
£442
£394
£374
£371
£190
0.0
2.5
5.0
7.5
10.0
12.5
Units Sold

10 Best Selling Products in Last 1 Year
Labels indicate revenue generated by the SKUs
Product ID and Description
SKU11130 Bra M purple
SKU13606 Cargo Pants S green
SKU10019 T−shirt M pink
Sandals M beige
SKU11698
SKU10078 T−shirt M beige
SKU11453 Boots M blue
SKU14362 Straight Leg Jeans M white
SKU13701 Chinos M black
302 Straight Leg Jeans M white
3398 Joggers S beige
£3022
£2630
£2432
£2373
£2346
£2280
£2232
£2184
£2108
£2106
0
1000
2000
3000
Revenue


10 Best Selling Categories in Last 1 Year
Labels indicate the revenue generated from category
Category Name
Innerwear Male Kids
Jackets Male Kids
Pants Female Pre−Teens
Jeans Female Pre−Teens
Innerwear Male Adults
Jeans Male Kids
Pants Male Kids
Shirts Female Kids
Dress Female Kids
wear Male Pre−Teens
£1210
£1104
£1094
£1081
£1062
£920
£899
£798
£737
£730
0
250
500
750
1000
1250
Revenue


Customer Acquisition in Last 1 Year
Labels indicate the number of new customer from each platform
New Customers
6
4
2
0
6
5
4
2
1
2
1
90 to 180 days
180 to 270 days
270 to 365 days
Acquisition Channel
PLATFORM
Facebook
Google Ads
Instagram
TikTok
X



Conclusion

This project implemented a thorough approach for data management for a UK-based apparel e-commerce store. The database structure, depicted conceptually through an ER diagram, featured eight principal entities: products, customers, shipments, promotions, advertisements, suppliers, categories, and transactions, implemented via a SQL schema. Synthetic data, simulating genuine retail transactions, was generated in R. Rigorous quality assurance procedures preceded data insertion into the database. Subsequent data analysis was conducted using Quarto with R to provide actionable insights for management. Automation of data validation, loading, and analysis processes via a GitHub workflow enabled multi-stakeholder oversight and accountability across all project phases.

References

- Betebenner, D.W. (2021) *Generate Random Given and Surnames [R package random- Names version 1.5-0.0]*. https://cran.r-project.org/web/packages/randomNames/index .html. [date accessed: 1 March 2024
- Walczak, E. (2021) *API Wrapper Around 'Postcodes.io'* [R package PostcodesioR version 0.3.1]. https://cran.r-project.org/web/packages/PostcodesioR/index.html.