Report pdf

There are two common workflows for data integration: ELT(Extract, Load, Transform) and ETL (Extract, Transform, Load)

The major difference between ELT and ETL is that in the ELT stage, normalization is performed after the datasets are imported into the database. In the ETL stage, the data is normalized and transformed before it is loaded into the database.

In our work, we chose ETL (Extract, Transform, Load) instead of ELT as our workflow and used SQL and R interchangeably to perform transformations. This is because we have found that ETL workflow is more suitable for small data sets, so we thought that it would be more compromised with our work.

Part 1: Database Design and Implementation

Task 1.1: E-R Diagram

Entities

Our E-R Diagram for an E-commerce database consisted of five main entities:

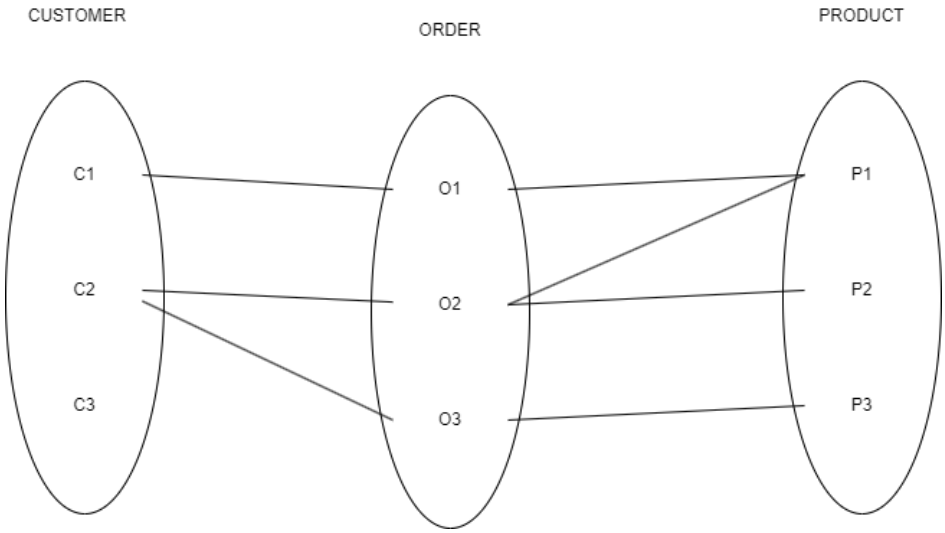
1. CUSTOMER: Represents details of individuals or entities who purchase products, including attributes such as customer ID, customer name, contact information, and gender.
2. PRODUCT: Represents details of items available for sale, including attributes such as product ID, product name, description, rating, price, and available stock.
3. ADVERTISEMENT: Represents details of promotional activities used to advertise products, including attributes such as advertisement ID, number of times the advertisement is shown, cost of the advertisement, and the place the advertisement was placed.
4. SUPPLIER: Represents details of entities providing products to businesses or customers, including attributes such as supplier ID, supplier name, and contact information.
5. CATEGORY: Represents product classifications or groupings, including attributes such as category unique ID, name, and fee amount as a percentage.

Relationships

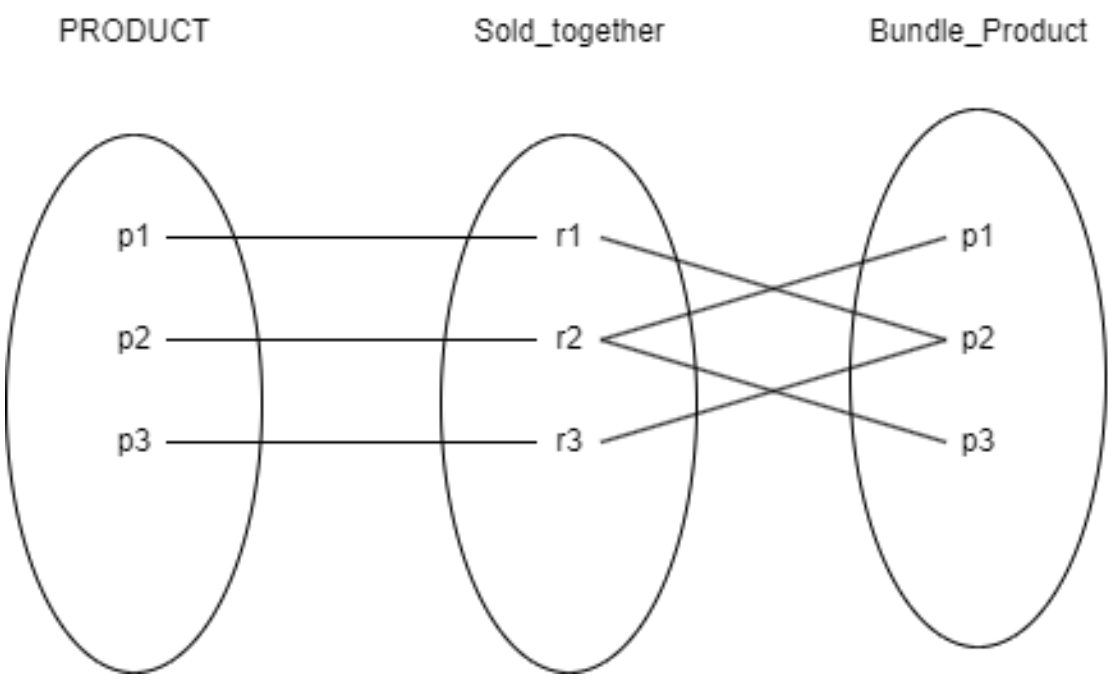
The relationships among these entities are as follows:

- CUSTOMER and PRODUCT have an M-N relationship meaning one customer can order many products, and one product can be ordered by many customers.

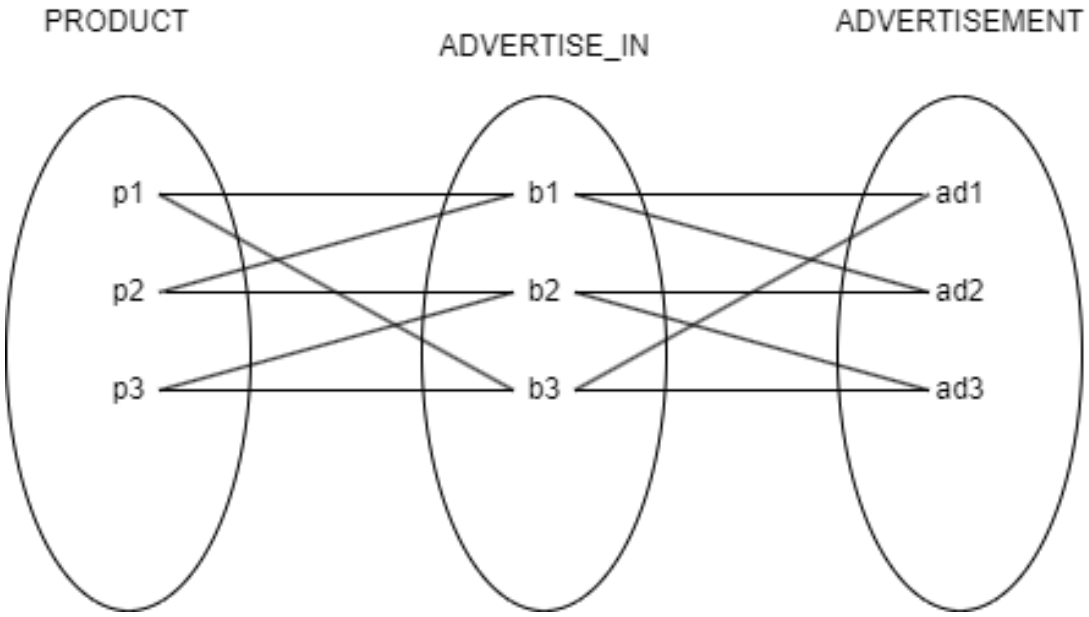
  The relationship is shown as ORDER, representing a customer placing an order to purchase products. It also contains some attributes to store the details of each order, including order ID, order date, order status, order quantity, promo code, payment method, and delivery fee.



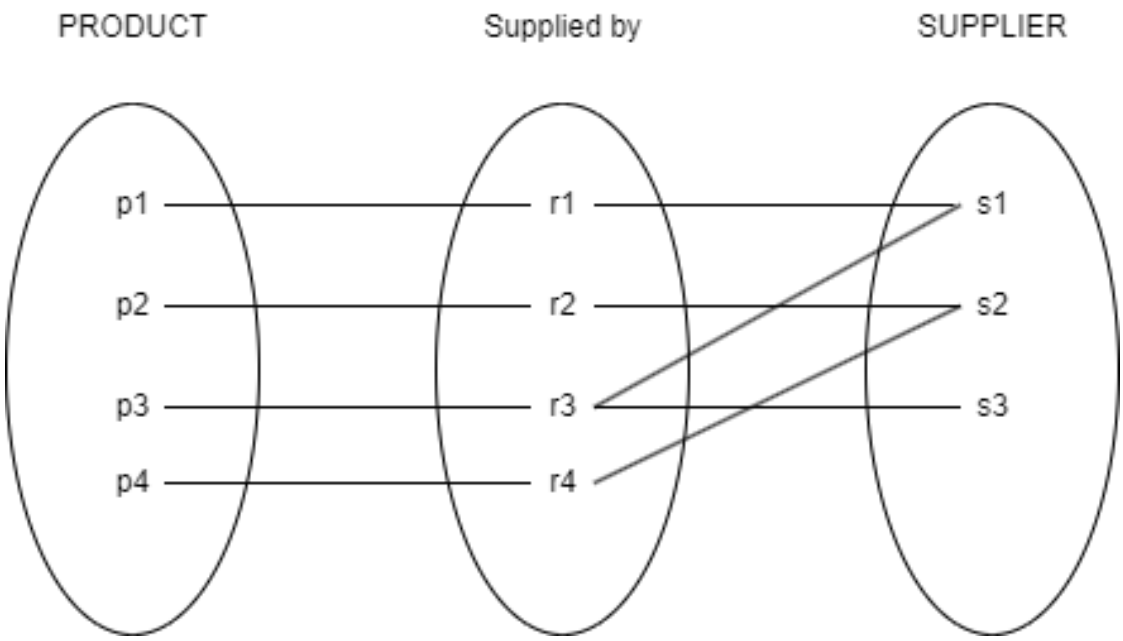
- PRODUCT has a self-referencing relationship of 1 to many. The relationship is shown as Sold_Together, indicating that one product can be sold together with others as a bundle.



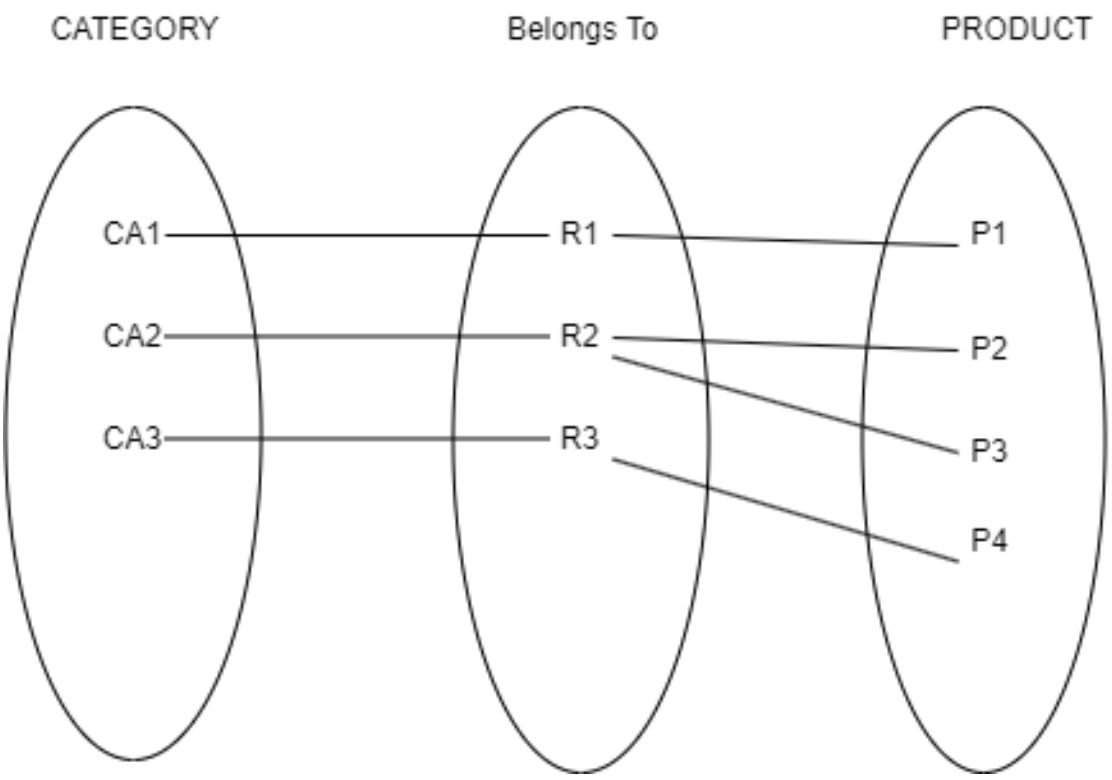
- PRODUCT and ADVERTISEMENT have an M-N relationship. This relationship is shown as ADVERTISE_IN to reflect products presented in the advertisements, meaning multiple advertisements can promote one product, and one advertisement can promote multiple products.



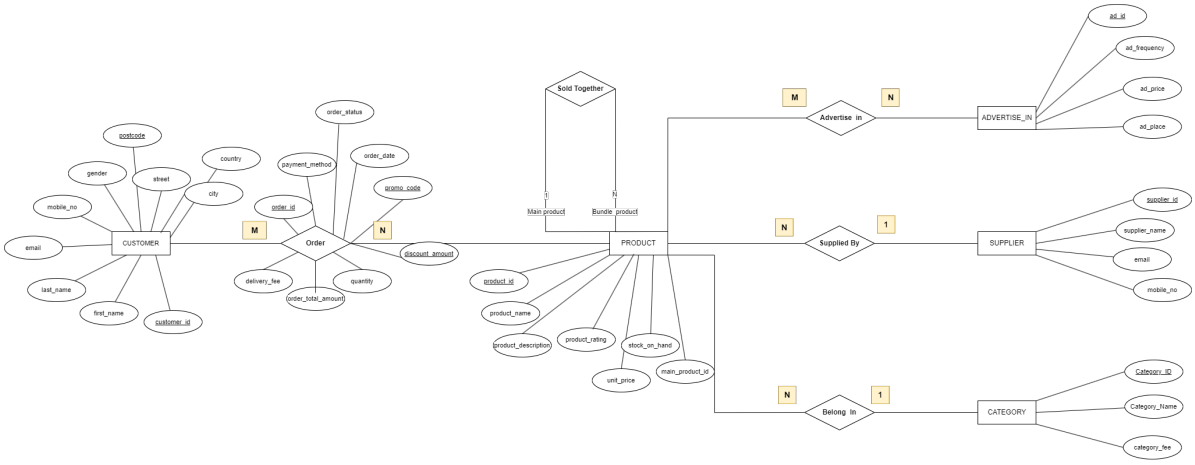
- PRODUCT and SUPPLIER have an N-1 relationship, indicating that one product can be supplied by only one supplier, but one supplier can provide multiple products.



- CATEGORY and PRODUCT have an 1-N relationship, meaning one product can belong to only one category, but one category can contain multiple products.



As a result, this is our E-R diagram.



Task 1.2: SQL Database Schema Creation

Normalization:

According to our first draft of the E-R diagram, two main adjustments were made in order to comply with 3NF

The first adjustment was on the ORDER table. After reviewing the order of normal forms, it was found that the ORDER entity still did not comply with 3NF.

Functional Dependency:

{order_id, customer_id, product_id } -> { order_date , order_status, order_quantity, promo_code, discount amount, payment_method, delivery_fee}

{promo_code} -> { discount_amount}

As we assumed that order_id could be duplicated to represent products ordered by the same customer simultaneously, there would be UPDATE anomalies. If there is an update on any attributes, such as payment_methods, we must alter more than one row in case there is more than one product in that order_id. In addition, discount_amount is also transitively dependent on promo_code.

Therefore, we separated the ORDER table into three entities including:

1. ORDER_DETAIL is similar to the ORDER table but has fewer attributes to contain each order's details. It has product_id as a primary key, customer_id and promo_code as foreign keys, and other attributes like order_date, order_status, and payment_method.
2. ORDER_ITEM contains product IDs and the quantities ordered in each order. The table has order_id and product_id as foreign keys and a composite primary key, and quantity as another attribute.
3. DISCOUNT is created to store the data of available promotional discounts, which consists of promo_code as a primary key and discount_amount.

The next adjustment was on the CUSTOMER table, which was initially on 2NF. Based on its function dependency, street, city, and country can also be determined by postcode and customer_id.

Functional Dependency:

{customer_id} ->{ first_name , last_name , gender , email, mobile_no , street , city , country , postcode } {postcode} -> { street, city , country }

This indicated that street, city, and country were transitively dependent on postcode. As a result, a new table is created as ADDRESS, which has postcode as a primary key and stores street, city, and country as other attributes.

In summary, four new entities were created from the normalization, which were ORDER_DETAIL, ORDER_ITEM, DISCOUNT, and ADDRESS. This resulted in a total of ten entities in our schema.

Logical Schema

According to the E-R diagram and normalization s, we can list the logical schema as follows:

- CUSTOMER(customer_id, first_name, last_name, gender, email, mobile_no, address_id)
- ADDRESS(address_id, postcode, street, city, country)
- DISCOUNT(promo_code, discount_amount)
- ADVERTISEMENT(ad_id, ad_frequency, ad_place, ad_price)
- SUPPLIER(supplier_id, supplier_name, email, mobile_no)
- CATEGORY(category_id, category_name, category_fee)
- PRODUCT(product_id, product_name, product_description, product_rating, unit_price, stock_at_hand, main_product_id, category_id, supplier_id)
- ORDER_DETAIL(order_id, customer_id, order_date, order_status, promo_code, payment_method, delivery_fee)
- ORDER_ITEM(order_id, product_id, quantity)
- ADVERTISE_IN(product_id, ad_id)

Physical Schema <update>

```
Warning: package 'RSQLite' was built under R version 4.3.2
```

```
Attaching package: 'dplyr'
```

```
The following objects are masked from 'package:stats':

    filter, lag
```

```
The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union
```

```
Attaching package: 'gridExtra'
```

```
The following object is masked from 'package:dplyr':

    combine
```

Firstly, we created a connection to our database named "database.db"

```
connect <- dbConnect(RSQLite::SQLite(), "database.db")
```

Then, we first created parent entities, including CUSTOMER, DISCOUNT, ADVERTISEMENT, SUPPLIER, and CATEGORY.

1. Create CUSTOMER entity

```
CREATE TABLE IF NOT EXISTS CUSTOMER (
  customer_id VARCHAR(50) PRIMARY KEY,
  first_name VARCHAR(50) NOT NULL,
  last_name VARCHAR(50) NOT NULL,
  gender VARCHAR(10),
  customer_email VARCHAR(50) NOT NULL UNIQUE,
  customer_mobile VARCHAR(15) NOT NULL UNIQUE,
  address_id VARCHAR(50) NOT NULL,
  FOREIGN KEY (address_id) REFERENCES ADDRESS (address_id)
);
```

2. Create ADDRESS entity

```
CREATE TABLE IF NOT EXISTS ADDRESS (
  address_id VARCHAR(50) PRIMARY KEY,
  postcode VARCHAR(20) NOT NULL,
  street VARCHAR(50) NOT NULL,
  city VARCHAR(100) NOT NULL,
  country VARCHAR(100) NOT NULL
  );
```

3. Create DISCOUNT entity

```
CREATE TABLE IF NOT EXISTS DISCOUNT (
  promo_code VARCHAR(20) PRIMARY KEY,
  discount_percent INT NOT NULL
);
```

4. Create ADVERTISEMENT entity

```
CREATE TABLE IF NOT EXISTS ADVERTISEMENT (
  ad_id VARCHAR(50) PRIMARY KEY,
  ad_frequency INT NOT NULL,
  ad_place VARCHAR(50) NOT NULL,
  ad_price DECIMAL(10, 2) NOT NULL
);
```

5. Create SUPPLIER entity

```
CREATE TABLE IF NOT EXISTS SUPPLIER (
  supplier_id VARCHAR(250) PRIMARY KEY,
  supplier_name VARCHAR(250) NOT NULL,
  supplier_email VARCHAR(250) NOT NULL,
  supplier_mobile VARCHAR(20) NOT NULL
);
```

6. Create CATEGORY entity

```
CREATE TABLE IF NOT EXISTS CATEGORY (
  category_id VARCHAR(50) PRIMARY KEY,
  category_name VARCHAR(50) NOT NULL,
  category_fee INT NOT NULL
);
```

Then, we created entities that are children entities and entities that have referential integrity, which consist of PRODUCT, ORDER_DETAIL, ORDER_ITEM, and ADVERTISE_IN

7. Create PRODUCT entity

```
CREATE TABLE IF NOT EXISTS PRODUCT (
  product_id VARCHAR(50) PRIMARY KEY,
  product_name VARCHAR(50) NOT NULL,
  product_description VARCHAR(50),
  product_rating DECIMAL(5,2),
  unit_price DECIMAL(10,2) NOT NULL,
  stock_on_hand INT NOT NULL,
  main_product_id VARCHAR(50),
  category_id VARCHAR(50) NOT NULL,
  supplier_id VARCHAR(50) NOT NULL,
  FOREIGN KEY (supplier_id) REFERENCES SUPPLIER (supplier_id),
  FOREIGN KEY (category_id) REFERENCES CATEGORY (category_id)
);
```

8. Create ORDER_DETAIL entity

```
CREATE TABLE IF NOT EXISTS ORDER_DETAIL (
  order_id VARCHAR(50) PRIMARY KEY,
  customer_id VARCHAR(50),
  order_date DATE NOT NULL,
  order_status VARCHAR(50) NOT NULL,
  promo_code VARCHAR(20),
  payment_method TEXT NOT NULL,
  delivery_fee DECIMAL(10, 2) NOT NULL,
  FOREIGN KEY (customer_id) REFERENCES CUSTOMER (customer_id),
  FOREIGN KEY (promo_code)  REFERENCES DISCOUNT (promo_code)
);
```

9. Create ORDER_ITEM entity

```
CREATE TABLE IF NOT EXISTS ORDER_ITEM (
  order_id VARCHAR(50),
  product_id VARCHAR(50),
  order_quantity INT NOT NULL,
  PRIMARY KEY (order_id, product_id),
  FOREIGN KEY (order_id)   REFERENCES ORDER_DETAIL (order_id)
  FOREIGN KEY (product_id) REFERENCES PRODUCT (product_id)
);
```

10. Create ADVERTISE_IN entity

```
CREATE TABLE IF NOT EXISTS ADVERTISE_IN (
  product_id VARCHAR(50),
  ad_id VARCHAR(50),
  PRIMARY KEY (product_id, ad_id),
  FOREIGN KEY (product_id) REFERENCES PRODUCT (product_id),
  FOREIGN KEY (ad_id)      REFERENCES ADVERTISEMENTS (ad_id)
);
```

Part 2: Data Generation and Implementation

Task 2.1: Synthetic Data Generation

The synthetic data of each table was created based on the normalised schema using Mockaroo, a mock data generator platform.

The number of observation data generated for each entity was as followed:

- 50 observations for ADDRESS

- 50 observations for ADVERTISE_IN
- 5 observations for ADVERTISEMENT
- 5 observations for CATEGORY
- 50 observations for CUSTOMER
- 5 observations for DISCOUNT
- 100 observations for ORDER_DETAIL
- 100 observations for ORDER_ITEM
- 50 observations for PRODUCT
- 50 observations for SUPPLIER

Task 2.2: Data Import and Quality Assurance

Data Import

Loading all generated data sets using read_csv to each entity

```
customer <- readr::read_csv("data_upload/CUSTOMER.csv")
```

```
Rows: 50 Columns: 7
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (7): customer_id, first_name, last_name, gender, customer_email, custome...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
address <- readr::read_csv("data_upload/ADDRESS.csv")
```

```
Rows: 50 Columns: 5
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (5): address_id, postcode, street, city, country

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
category <- readr::read_csv("data_upload/CATEGORY.csv")
```

```
Rows: 5 Columns: 3
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): category_id, category_name
dbl (1): category_fee

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
supplier <- readr::read_csv("data_upload/SUPPLIER.csv")
```

```
Rows: 50 Columns: 4
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (4): supplier_id, supplier_name, supplier_email, supplier_mobile

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
discount <- readr::read_csv("data_upload/DISCOUNT.csv")
```

```
Rows: 5 Columns: 2
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (1): promo_code
dbl (1): discount_percent

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
product <- readr::read_csv("data_upload/PRODUCT.csv")
```

```
Rows: 50 Columns: 9
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (6): product_id, category_id, supplier_id, product_name, product_descrip...
dbl (3): product_rating, unit_price, stock_on_hand
```

```
i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
order_item <- readr::read_csv("data_upload/ORDER_ITEM.csv")
```

```
Rows: 200 Columns: 3
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): order_id, product_id
dbl (1): order_quantity

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
order_detail <- readr::read_csv("data_upload/ORDER_DETAIL.csv")
```

```
Rows: 100 Columns: 7
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (6): order_id, customer_id, order_date, order_status, promo_code, paymen...
dbl (1): delivery_fee

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
advertisement <- readr::read_csv("data_upload/ADVERTISEMENT.csv")
```

```
Rows: 5 Columns: 4
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): ad_id, ad_place
dbl (2): ad_frequency, ad_price

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
advertise_in <- readr::read_csv("data_upload/ADVERTISE_IN.csv")
```

```
Rows: 50 Columns: 2
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): product_id, ad_id

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Quality Assurance

The imported data sets were validated before being added to the database to ensure they aligned with the nature of the keys and data type specified in the physical schema. First, we validated parent entities CUSTOMER, SUPPLIER, CATEGORY, ADVERTISEMENT, and DISCOUNT. Once all parent entities were validated, we continued validating child entities PRODUCT, ORDER_ITEM, ORDER_DETAIL, and ADVERTISE_IN.

Parent Entities Validation

1. CUSTOMER

   Validation processes for CUSTOMER entity included:

   - Check if the values of the primary key are unique
   - Check the format of the customers' first and last names. The format is expected to be first uppercase alphabet followed by lowercase alphabet.
   - Check the format of the email
   - Check the format of the mobile number, which should start with a plus sign followed by 12 integer values
   - Check if there are any values of a foreign key, which is address_id, in the CUSTOMER table that do not exist in the ADDRESS table.
   - Check if there is any missing data in the attributes that should not have missing values
   - Remove unqualified data values

```r
#Check duplicate pk
duplicate_customer_id <- customer[duplicated(customer$customer_id), "customer_id"]

#Check format of first and last name (1st alphabet is uppercase, rest is lowercase)
invalid_customer_firstname <- customer[!grepl("^[A-Z][a-z]*$", customer$first_name), c('
invalid_customer_lastname <- customer[!grepl("^[A-Z][a-z]*$", customer$last_name), c("cu
```

```
#Check email format
invalid_customer_email <- customer[!grepl("^[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\\.[A-Za-z]{

#Check format of mobile number (+xx xxx xxx xxxx)
invalid_customer_mobile <- customer[!grepl("^\\+\\d{1,3}\\s[0-9]{3}\\s[0-9]{3}\\s[0-9]{4

#Check if address_id exists in the ADDRESS table
invalid_address_fk <- customer[!customer$address_id %in% address$address_id, c("customer

#Check for missing data
na_customer_customer_id <- customer[is.na(customer$customer_id), "customer_id"]
na_customer_first_name <- customer[is.na(customer$first_name), c("customer_id", "first_n
na_customer_last_name <- customer[is.na(customer$last_name), c("customer_id", "last_name
na_customer_customer_email <- customer[is.na(customer$customer_email), c("customer_id",
na_customer_customer_mobile <- customer[is.na(customer$customer_mobile), c("customer_id"

#Remove unclean data
bad_customer_record <- unique(c(duplicate_customer_id$customer_id,
                                invalid_customer_firstname$customer_id,
                                invalid_customer_lastname$customer_id,
                                invalid_customer_email$customer_id,
                                invalid_customer_mobile$customer_id,
                                invalid_address_fk$customer_id,
                                na_customer_customer_id$customer_id,
                                na_customer_first_name$customer_id,
                                na_customer_last_name$customer_id,
                                na_customer_customer_email$customer_id,
                                na_customer_customer_mobile$customer_id))
customer <- customer[!(customer$customer_id %in% bad_customer_record), ]
```

2. ADDRESS

   Validation processes for CUSTOMER entity included:

   - Check if the values of the primary key are unique
   - Check if there is any missing data in the attributes that should not have missing values
   - Remove unqualified data values

```
#Check duplicate pk
duplicate_address_id <- address[duplicated(address$address_id), "address_id"]
```

```
#Check for missing data
na_address_address_id <- address[is.na(address$address_id), "address_id"]
na_address_postcode <- address[is.na(address$postcode), c("address_id", "postcode")]
na_address_street <- address[is.na(address$street), c("address_id", "street")]
na_address_city <- address[is.na(address$city), c("address_id", "city")]
na_address_country <- address[is.na(address$country), c("address_id", "country")]

#Remove unclean data
bad_address_record <- unique(c(duplicate_address_id$address_id,
                               na_address_address_id$address_id,
                               na_address_postcode$address_id,
                               na_address_street$address_id,
                               na_address_city$address_id,
                               na_address_country$address_id))
address <- address[!(address$address_id %in% bad_address_record), ]
```

3. CATEGORY

   Validation processes for SUPPLIER entity included:

   - Check if the values of the primary key are unique
   - Check the datatype of categories' names.
   - Check if there is any missing data in the attributes that should not have missing values
   - Remove unqualified data value

```
#Check duplicate pk
duplicate_category_id <- category[duplicated(category$category_id), "category_id"]

#Check category (can contain alphabets)
invalid_category_name <- category[!grepl("^[A-Za-z]+( [A-Za-z]+)*$", category$category_n

#Check for duplicate category name
duplicate_category_name <- category[duplicated(category$category_name), c("category_id",

#Check for negative prices
negative_category_fee <- category[category$category_fee < 0, c("category_id", "category_

#Check for missing data
na_category_category_id <- category[is.na(category$category_id), "category_id"]
na_category_category_name <- category[is.na(category$category_name), c("category_id", "c
na_category_category_fee <- category[is.na(category$category_fee), c("category_id", "cat
```

```
#Remove unclean data
bad_category_record <- unique(c(duplicate_category_id$category_id,
                                invalid_category_name$category_id,
                                duplicate_category_name$category_id,
                                negative_category_fee$category_id,
                                na_category_category_id$category_id,
                                na_category_category_name$category_id,
                                na_category_category_fee$category_id))
category <- category[!(category$category_id %in% bad_category_record), ]
```

4. SUPPLIER

   Validation processes for SUPPLIER entity included:

   - Check if the values of the primary key are unique
   - Check the format of suppliers' names.
   - Check the format of the email
   - Check the format of the mobile number, which should start with a plus sign followed by 12 integer values
   - Check if there is any missing data in the attributes that should not have missing values
   - Remove unqualified data value

```
#Check duplicate pk
duplicate_supplier_id <- supplier[duplicated(supplier$supplier_id), "supplier_id"]

#Check supplier (can contain alphabets, comma, hyphen, dot)
invalid_supplier_name <- supplier[!grepl("^[A-Za-z,.-]+( [A-Za-z,.-]+)*$", supplier$supp

#Check email format
invalid_supplier_email <- supplier[!grepl("^[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\\.[A-Za-z]{

#Check format of mobile number (+xx xxx xxx xxxx)
invalid_supplier_mobile <- supplier[!grepl("^^\\+\\d{1,3}\\s[0-9]{3}\\s[0-9]{3}\\s[0-9]{

#Check for missing data
na_supplier_supplier_id <- supplier[is.na(supplier$supplier_id), "supplier_id"]
na_supplier_supplier_name <- supplier[is.na(supplier$supplier_name), c("supplier_id", "s
na_supplier_supplier_email <- supplier[is.na(supplier$supplier_email), c("supplier_id",
na_supplier_supplier_mobile <- supplier[is.na(supplier$supplier_mobile), c("supplier_id"
```

```
#Remove unclean data
bad_supplier_record <- unique(c(duplicate_supplier_id$supplier_id,
                                invalid_supplier_name$supplier_id,
                                invalid_supplier_email$supplier_id,
                                invalid_supplier_mobile$supplier_id,
                                na_supplier_supplier_id$supplier_id,
                                na_supplier_supplier_name$supplier_id,
                                na_supplier_supplier_email$supplier_id,
                                na_supplier_supplier_mobile$supplier_id))
supplier <- supplier[!(supplier$supplier_id %in% bad_supplier_record), ]
```

5. ADVERTISEMENT

   Validation processes for the ADVERTISEMENT entity included:

   - Check if the values of the primary key are unique
   - Check the datatype of ad_frequency, which should be integers
   - Check if there is any negative value in the attributes that the values should only be positive
   - Check if there is any missing data in the attributes that should not have missing values
   - Remove unqualified data value

```
#Check duplicate pk
duplicate_ad_id <- advertisement[duplicated(advertisement$ad_id), "ad_id"]

#Check ad frequency (can only contain integer)
invalid_ad_frequency <- advertisement[!grepl("^[0-9]+$", advertisement$ad_frequency)

#Check for negative ad frequency
negative_ad_frequency <- advertisement[advertisement$ad_frequency < 0, c("ad_id", "a

#Check for negative prices
negative_ad_prices <- advertisement[advertisement$ad_price < 0, c("ad_id", "ad_price

#Check for missing data
na_advertisement_ad_id <- advertisement[is.na(advertisement$ad_id), "ad_id"]
na_advertisement_ad_frequency <- advertisement[is.na(advertisement$ad_frequency), c
na_advertisement_ad_price <- advertisement[is.na(advertisement$ad_price), c("ad_id"
na_advertisement_ad_place <- advertisement[is.na(advertisement$ad_place), c("ad_id"
```

```
#Remove unclean data
bad_advertisement_record <- unique(c(duplicate_ad_id$ad_id,
                                     invalid_ad_frequency$ad_id,
                                     negative_ad_frequency$ad_id,
                                     negative_ad_prices$ad_id,
                                     na_advertisement_ad_id$ad_id,
                                     na_advertisement_ad_frequency$ad_id,
                                     na_advertisement_ad_price$ad_id,
                                     na_advertisement_ad_place$ad_id))
advertisement <- advertisement[!(advertisement$ad_id %in% bad_advertisement_record)
```

6. DISCOUNT

   Validation processes for DISCOUNT entity included:

   - Check if the values of the primary key are unique
   - Check the datatype of discount_amount, which should be integers
   - Check if there is any missing data in the attributes that should not have missing values
   - Remove unqualified data value

```
#Check duplicate pk
duplicate_promo_code <- discount[duplicated(discount$promo_code), "promo_code"]

#Check percent
invalid_discount_percent <- discount[!grepl("^[0-9]+$", discount$discount_percent),

#Check for missing data
na_discount_promo_code <- discount[is.na(discount$promo_code), "promo_code"]
na_discount_discount_percent <- discount[is.na(discount$discount_percent), c("promo_

#Remove unclean data
bad_discount_record <- unique(c(duplicate_promo_code$promo_code,
                                invalid_discount_percent$promo_code,
                                na_discount_promo_code$promo_code,
                                na_discount_discount_percent$promo_code))
discount <- discount[!(discount$promo_code %in% bad_discount_record), ]
```

Children Entities Validation

7. PRODUCT

   Validation processes for PRODUCT entity included:

- Check if the values of the primary key are unique
- Check the datatype of product_name
- Check if there is any negative value in unit_price where the values should only be positive
- Check on the validity of stock_on_hand to see if there are any missing or negative values
- Check if there are any values of foreign keys, including supplier_id and category_id, in the PRODUCT table that do not exist in the SUPPLIER and CATEGORY table.
- Check if the values in main_product_id are self-referential to product_id and ensure that the values differ from those of product_id.
- Check if there is any missing data in the attributes that should not have missing values
- Remove unqualified data value

```
#Check duplicate pk
duplicate_product_id <- product[duplicated(product$product_id), "product_id"]

#Check product name (can contain alphabets, comma, hyphen, dot)
invalid_product_name <- product[!grepl("^[A-Za-z,.-]+( [A-Za-z,.-]+)*$", product$pro

#Check for negative prices
negative_unit_prices <- product[product$unit_price < 0, c("product_id", "unit_price"

#Check invalid stock
invalid_stock <- product[!grepl("^[0-9]+$", product$stock_on_hand), c("product_id",
negative_stock <- product[product$stock_on_hand < 0, c("product_id", "stock_on_hand"

#Check if supplier_id exists in the SUPPLIER table
invalid_supplier_fk <- product[!product$supplier_id %in% supplier$supplier_id, c("pr

#Check if category_id exists in the CATEGORY table
invalid_category_fk <- product[!product$category_id %in% category$category_id, c("pr

#Check if main product is self referential and it cannot be the same as product_id
invalid_main_product_ids <- product[!is.na(product$main_product_id) &
                                    !(product$main_product_id %in% product$product
                                        product$main_product_id != product$product


#Check for missing data
```

```
na_product_product_id <- product[is.na(product$product_id), "product_id"]
na_product_category_id <- product[is.na(product$category_id), c("product_id", "categ
na_product_supplier_id <- product[is.na(product$supplier_id), c("product_id", "suppl
na_product_product_name <- product[is.na(product$product_name), c("product_id", "pro
na_product_unit_price <- product[is.na(product$unit_price), c("product_id", "unit_pr
na_product_stock_on_hand <- product[is.na(product$stock_on_hand), c("product_id", "s

#Remove unclean data
bad_product_record <- unique(c(duplicate_product_id$product_id,
                               invalid_product_name$product_id,
                               negative_unit_prices$product_id,
                               invalid_stock$product_id,
                               negative_stock$product_id,
                               invalid_supplier_fk$product_id,
                               invalid_category_fk$product_id,
                               invalid_main_product_ids$product_id,
                               na_product_product_id$product_id,
                               na_product_category_id$product_id,
                               na_product_supplier_id$product_id,
                               na_product_product_name$product_id,
                               na_product_unit_price$product_id,
                               na_product_stock_on_hand$product_id))
product <- product[!(product$product_id %in% bad_product_record), ]
```

8. ORDER_ITEM

   Validation processes for ORDER_ITEM entity included:

   - Check if the values of the primary key are unique
   - Check if there are any values of foreign keys, including customer_id and promo_code, in the ORDER_ITEM table that do not exist in the CUSTOMER and DISCOUNT table.
   - Check on the values of order_status. The values of this attribute are expected to be Pending, Paid, Shipped, Complete, or Cancelled
   - Check on the values of payment_method. The values of this attribute are expected to be Mastercard, Visa, or Amex
   - Check on the date format
   - Check if there is any negative value in delivery_fee where the values should only be positive

- Check if there is any missing data in the attributes that should not have missing values
- Remove unqualified data value

```
#Check duplicate pk
duplicate_order_id <- order_detail[duplicated(order_detail$order_id), "order_id"]

#Check if customer_id exists in the CUSTOMER table
invalid_customer_fk <- order_detail[!order_detail$customer_id %in% customer$customer_id,

#Check if promo_code exists in the DISCOUNT table
discounted_order <- order_detail[!is.na(order_detail$promo_code), ]
invalid_promo_fk <- discounted_order[!discounted_order$promo_code %in% discount$promo_co

#Check order status
status <- c("Pending", "Paid", "Shipped", "Completed", "Cancelled")
invalid_order_status <- order_detail[!order_detail$order_status %in% status, c("order_id

#Check payment method
payment <- c("Mastercard", "Visa", "Amex")
invalid_payment_method <- order_detail[!order_detail$payment_method %in% payment, c("orc

#Check date format (dd/mm/yyyy)
invalid_order_date <- order_detail[!grepl("^\\d{2}/\\d{2}/\\d{4}$", order_detail$order_d

#Check for negative delivery fee
negative_delivery_fee <- order_detail[order_detail$delivery_fee < 0, c("order_id", "deli

#Check for missing data
na_order_order_id <- order_detail[is.na(order_detail$order_id), "order_id"]
na_order_customer_id <- order_detail[is.na(order_detail$customer_id), c("order_id", "cus
na_order_order_status <- order_detail[is.na(order_detail$order_status), c("order_id", "o
na_order_order_date <- order_detail[is.na(order_detail$order_date), c("order_id", "order
na_order_payment_method <- order_detail[is.na(order_detail$payment_method), c("order_id"
na_order_delivery_fee <- order_detail[is.na(order_detail$delivery_fee), c("order_id", "o

#Remove unclean data
bad_order_record <- unique(c(duplicate_order_id$order_id,
                             invalid_customer_fk$order_id,
                             invalid_promo_fk$order_id,
                             invalid_order_status$order_id,
                             invalid_payment_method$order_id,
```

```
                                invalid_order_date$order_id,
                                negative_delivery_fee$order_id,
                                na_order_order_id$order_id,
                                na_order_customer_id$order_id,
                                na_order_order_status$order_id,
                                na_order_order_date$order_id,
                                na_order_payment_method$order_id,
                                na_order_delivery_fee$order_id))
order_detail <- order_detail[!(order_detail$order_id %in% bad_order_record), ]
```

9. ORDER_DETAIL

   Validation processes for ORDER_DETAIL entity included:

   - Check if the values of the primary key are unique
   - Check if there are any values of foreign keys, including order_id and product_id, in the ORDER_DETAIL table that do not exist in the ORDER_ITEM and PRODUCT table.
   - Check on the validity of order_quantity to see if there are any missing or negative values
   - Check if there is any missing data in the attributes that should not have missing values
   - Remove unqualified data value

```
#Check duplicate for composite primary key
order_item_composite <- paste(order_item$order_id, order_item$product_id)
duplicate_order_item_composite <- order_item[duplicated(order_item_composite), c("order_

#Check if order_id exists in the ORDER_ITEM table
invalid_order_fk <- order_item[!order_item$order_id %in% order_detail$order_id, c("order

#Check if product_id exists in the PRODUCT table
invalid_product_fk <- order_item[!order_item$product_id %in% product$product_id, c("orde

#Check invalid order quantity
invalid_quantity <- order_item[!grepl("^[0-9]+$", order_item$order_quantity), c("order_i
negative_zero_quantity <- order_item[order_item$order_quantity < 1, c("order_id", "order

#Check for missing data
na_order_item_order_id <- order_item[is.na(order_item$order_id), "order_id"]
na_order_item_product_id <- order_item[is.na(order_item$order_id), c("order_id", "produc
```

```
na_order_item_order_quantity <- order_item[is.na(order_item$order_quantity), c("order_id

#Remove unclean data
bad_order_item_record <- unique(c())
order_item <- order_item[!(order_item$order_id %in% bad_order_item_record), ]

#Remove unclean data
# Combine all unclean data
bad_order_item_record <- rbind(duplicate_order_item_composite,
                               invalid_order_fk,
                               invalid_product_fk,
                               invalid_quantity,
                               negative_zero_quantity,
                               na_order_item_order_id,
                               na_order_item_product_id,
                               na_order_item_order_quantity)

# Remove duplicates from bad records
bad_order_item_record <- unique(bad_order_item_record)

# Remove unclean data based on composite key
order_item <- order_item[!paste(order_item$order_id, order_item$product_id) %in% paste(b
```

10. ADVERTISE_IN

    Validation processes for ADVERTISE_IN entity included:

    - Check if the values of the composite primary key are unique
    - Check if there are any values of foreign keys, including ad_id and product_id, in the ADVERTISE_IN table that do not exist in the ADVERTISEMENT and PRODUCT table.
    - Check if there is any missing data in the attributes that should not have missing values
    - Remove unqualified data value

```
#Check duplicate for composite primary key
advertise_in_composite <- paste(advertise_in$ad_id, advertise_in$product_id)
duplicate_advertise_in_composite <- advertise_in[duplicated(advertise_in_composite), c('

#Check if ad_id exists in the ADVERTISEMENT table
invalid_advertisement_fk <- advertise_in[!advertise_in$ad_id %in% advertisement$ad_id, c
```

```
#Check if product_id exists in the PRODUCT table
invalid_product_fk <- advertise_in[!advertise_in$product_id %in% product$product_id, c('

#Check for missing data
na_advertise_in_ad_id <- advertise_in[is.na(advertise_in$ad_id), "ad_id"]
na_advertise_in_product_id <- advertise_in[is.na(advertise_in$product_id), c("ad_id", "p

#Remove unclean data
# Combine all unclean data
bad_advertise_in_record <- rbind(duplicate_advertise_in_composite,
                                 invalid_advertisement_fk,
                                 invalid_product_fk,
                                 na_advertise_in_ad_id,
                                 na_advertise_in_product_id)

# Remove duplicates from bad records
bad_advertise_in_record <- unique(bad_advertise_in_record)

# Remove unclean data based on composite key
advertise_in <- advertise_in[!paste(advertise_in$ad_id, advertise_in$product_id) %in% pa
```

```
#add new records into table
connect <- dbConnect(RSQLite::SQLite(), "database.db")

tables <- c("CUSTOMER", "ADDRESS", "CATEGORY", "SUPPLIER", "PRODUCT", "DISCOUNT",
            "ORDER_ITEM", "ORDER_DETAIL", "ADVERTISEMENT", "ADVERTISE_IN")

table_new <- list(customer, address, category, supplier, product, discount,
                  order_item, order_detail, advertisement, advertise_in)

# Loop through each table
for (i in seq_along(tables)) {
  table <- tables[i]
  new_records <- table_new[[i]]

  # Read existing records from the table
  existing <- dbGetQuery(connect, paste("SELECT * FROM", table))

  # Convert data types if needed (e.g., order_date column)
  if ("order_date" %in% colnames(existing)) {
    existing$order_date <- as.character(existing$order_date)
    new_records$order_date <- as.character(new_records$order_date)
```

```
  }

  # Find new records not present in existing table
  new <- anti_join(new_records, existing)

  # Append new records to the table
  if (nrow(new) > 0) {
    dbWriteTable(connect, table, new, append = TRUE)
  }}
```

```
Joining with `by = join_by(customer_id, first_name, last_name, gender,
customer_email, customer_mobile, address_id)`
Joining with `by = join_by(address_id, postcode, street, city, country)`
Joining with `by = join_by(category_id, category_name, category_fee)`
Joining with `by = join_by(supplier_id, supplier_name, supplier_email,
supplier_mobile)`
Joining with `by = join_by(product_id, category_id, supplier_id, product_name,
product_description, product_rating, unit_price, stock_on_hand,
main_product_id)`
Joining with `by = join_by(promo_code, discount_percent)`
Joining with `by = join_by(order_id, product_id, order_quantity)`
Joining with `by = join_by(order_id, customer_id, order_date, order_status,
promo_code, payment_method, delivery_fee)`
Joining with `by = join_by(ad_id, ad_frequency, ad_place, ad_price)`
Joining with `by = join_by(product_id, ad_id)`
```

Part 3: Data Pipeline Generation

Task 3.1: GitHub Repository and Workflow Setup

We first created a new public repository named **DM_Group3** on GitHub and created the following files:

1. **README** file to include all student ID numbers of our group.
2. **database_schema** file to create a database and build the database schema.
3. **data_validation_and_load** file to create code for validating data and loading the cleaned data into the database.
4. **data_analysis** file to perform data analysis and visualise essential results.
5. two folders, named **data_upload** to store 10 datasets generated by Mockaroo, and **images** to store E-R diagrams.
6. **Report** as a qmd. file to report the tasks and how they were done.

Secondly, we create a new project in RStudio and connect it to Git for version control to manage code in a local development environment, leading to easier tracking of changes, creating branches, merging code, etc.

For setting up workflow, as GitHub Actions can automate workflows, such as running tests, building, and deploying tasks after pushing code, which can improve development efficiency and ensure code stability, we created the **.github/workflows** directory and an **etl.yaml** file within it.

Task 3.2: Data Import and Quality Assurance

Our GitHub Actions workflow was designed to execute a task named "ETL workflow for group 3.", triggering by pushing events to the 'main' branch. In this part, we defined a sequence of steps to be executed on the latest version of Ubuntu:

1. Use GitHub Actions checkout action to check out code into the working directory.
2. Set up R environment and specify the R version as '4.3.3'.
3. Cache R packages to avoid reinstalling them on each run.
4. Install required packages if the cache misses.
5. Run database_schema.Rmd to render database schema.
6. Run data_validation_and_load.Rmd to render validation and load data into database.
7. Run data_analysis.Rmd to render data analysis.
8. Utilize an authentication token to push changes to the 'main' branch.

Part 4: Data Analysis and Reporting with Quarto in R

Task 4.1: Advanced Data Analysis in R

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

```
Warning: package 'plotly' was built under R version 4.3.3
```

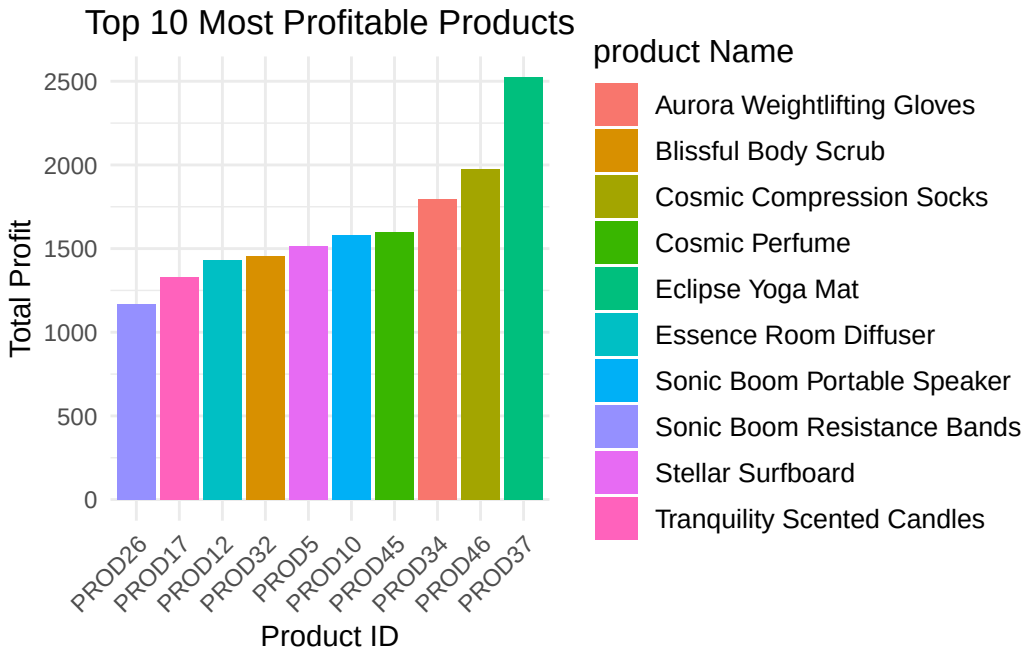
```
Attaching package: 'plotly'
```

```
The following object is masked from 'package:ggplot2':

    last_plot

The following object is masked from 'package:stats':

    filter

The following object is masked from 'package:graphics':

    layout
```

```r
# Connecting to the database
connect <- dbConnect(RSQLite::SQLite(), "database.db")
```

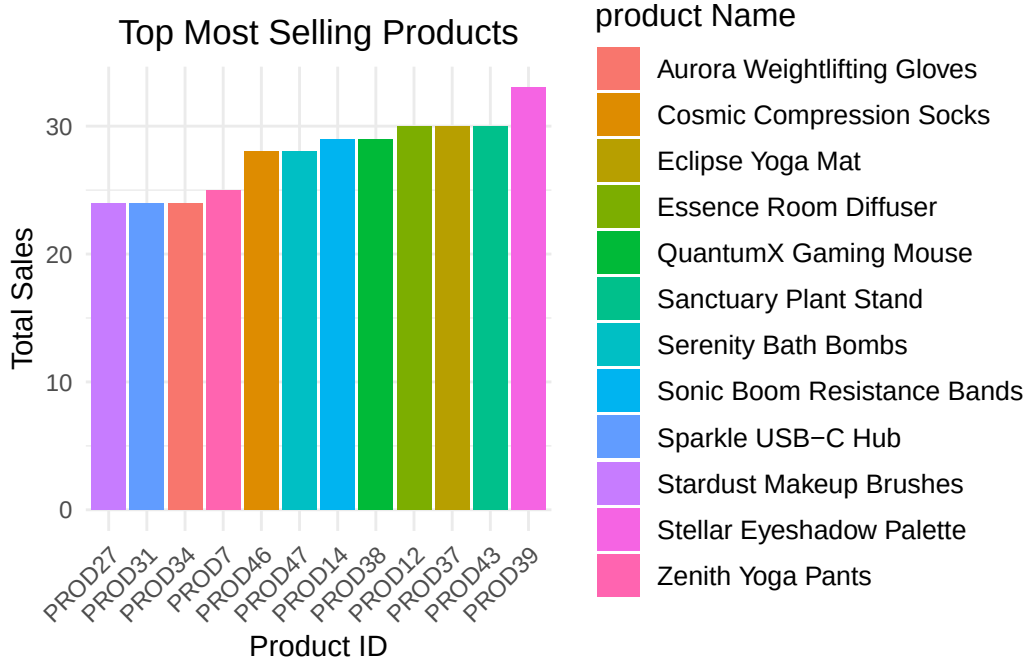
```r
# Report 1

# Top 10 products based on the Profit Generated

# Getting the tables from the database
product <- RSQLite::dbGetQuery(connect,'SELECT * FROM PRODUCT')
order_item <- RSQLite::dbGetQuery(connect,'SELECT * FROM ORDER_ITEM')
order_detail <- RSQLite::dbGetQuery(connect,'SELECT * FROM ORDER_DETAIL')
discount <- RSQLite::dbGetQuery(connect,'SELECT * FROM DISCOUNT')
# Creating a profit table that includes a total_profit (quantity x unit price) column for ea

profit_data <- order_item %>%
  inner_join(order_detail, by = "order_id") %>%
  filter(order_status != "Cancelled") %>%
  inner_join(product, by = "product_id") %>%
  left_join(discount, by = c("promo_code" = "promo_code")) %>%
  mutate(
    discount_percentage = ifelse(is.na(discount_percent), 0, discount_percent),
    total_profit = (order_quantity * unit_price) * (1 - discount_percentage / 100)
  ) %>%
  group_by(product_id, product_name) %>%
  summarise(
    total_profit = sum(total_profit),
    .groups = 'drop'
  ) %>%
  arrange(desc(total_profit)) # Arranging the total_profit from highest to lowest
```

```r
# Selecting the top 10 profitable products
top_10_profit_data <- head(profit_data, 10)


# Visualizing the results
ggplot(top_10_profit_data, aes(x = reorder(product_id, total_profit), y = total_profit, fill
  geom_bar(stat = "identity") +
  scale_fill_discrete(name = "product Name") +
  labs(title = "Top 10 Most Profitable Products", x = "Product ID", y = "Total Profit") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        legend.title = element_text(size = 12),
        legend.text = element_text(size = 10),
        plot.title = element_text(hjust = 0.5))
```




```r
# Top Most Selling Products

# Creating a sales that that includes the total quantity sold for each product and selecting
sales_data <- order_item %>%
  group_by(product_id) %>%
  summarise(Total_Sales = sum(order_quantity, na.rm = TRUE)) %>%
  arrange(desc(Total_Sales))
```

```r
top_selling_products <- sales_data %>%
  left_join(product, by = "product_id") %>%
  select(product_id, product_name, Total_Sales) %>%
  top_n(10, Total_Sales)

# Visualizing the results
ggplot(top_selling_products, aes(x = reorder(product_id, Total_Sales), y = Total_Sales, fill
  geom_bar(stat = "identity") +
  scale_fill_discrete(name = "product Name") +
  labs(title = "Top Most Selling Products", x = "Product ID", y = "Total Sales") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        legend.title = element_text(size = 12),
        legend.text = element_text(size = 10),
        plot.title = element_text(hjust = 0.5))
```



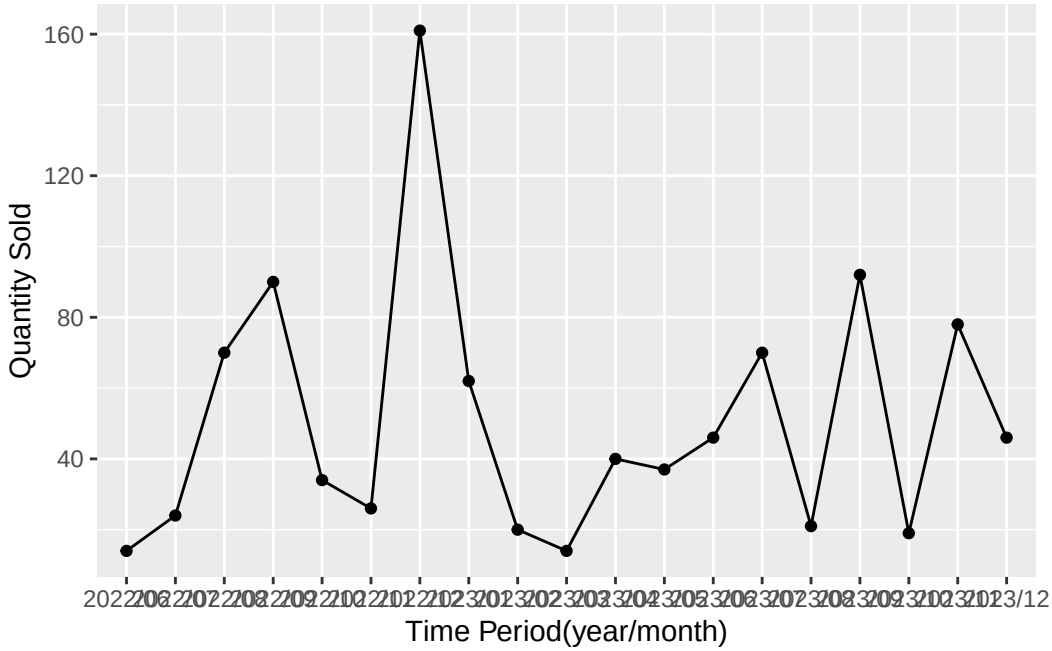

```r
#Report 2

# Bundles vs Individual products Comparison by Sales Volume

# Join product with order item
product_order_item <- order_item %>%
```

```r
  inner_join(product, by = "product_id")

# Calculate total quantity sold for bundled products
bundled_sales <- product_order_item %>%
  filter(!is.na(main_product_id)) %>%
  group_by(main_product_id) %>%
  summarise(Total_Quantity_Sold = sum(order_quantity, na.rm = TRUE)) %>%
  ungroup() %>%
  mutate(Product_Type = "Bundled")

# Calculate total quantity sold for individual products
individual_sales <- product_order_item %>%
  filter(is.na(main_product_id)) %>%
  group_by(product_id) %>%
  summarise(Total_Quantity_Sold = sum(order_quantity, na.rm = TRUE)) %>%
  ungroup() %>%
  mutate(Product_Type = "Individual")

# Combining the results
total_sales_by_type <- bind_rows(bundled_sales, individual_sales) %>%
  group_by(Product_Type) %>%
  summarise(Total_Quantity_Sold = sum(Total_Quantity_Sold, na.rm = TRUE)) %>%
  ungroup()

print(total_sales_by_type)
```

```
# A tibble: 2 x 2
  Product_Type Total_Quantity_Sold
  <chr>                      <int>
1 Bundled                      501
2 Individual                   463
```

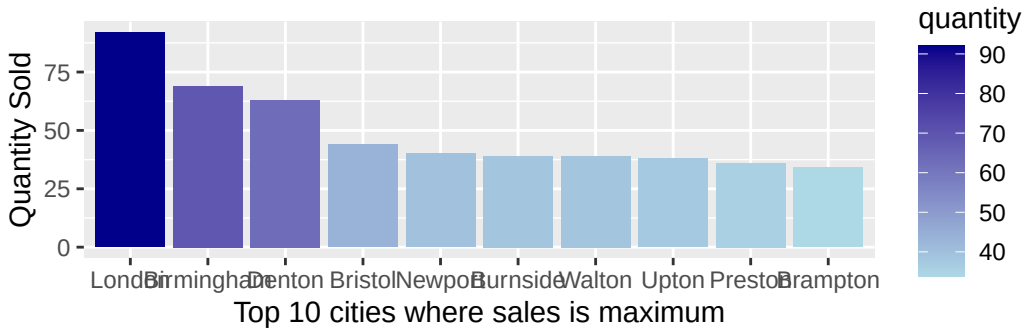
```r
# Visualizing the results
ggplot(total_sales_by_type, aes(x = Product_Type, y = Total_Quantity_Sold, fill = Product_Ty
  geom_bar(stat = "identity", width = 0.5) +  # Adjust width here
  scale_fill_manual(values = c("Bundled" = "skyblue", "Individual" = "salmon")) +
  labs(title = "Total Quantity Sold by Product Type",
       x = "Product Type",
       y = "Total Quantity Sold") +
  theme_minimal() +
  theme(legend.position = "none")
```


```
#SQL Query to get the sales over a time period

time_period_sales<- RSQLite::dbGetQuery(connect,'SELECT ORDITM.order_id, order_quantity,orde
#test

#Conversion of order_date field to appropiate format
time_period_sales$order_date <- as.Date(time_period_sales$order_date, format="%d/%m/%Y")

time_period_sales$order_date_mnth_yr <- format(time_period_sales$order_date,'%Y/%m')

#Conversion of order_date field to factors with levels

time_period_sales$order_date_mnth_yr <- factor(time_period_sales$order_date_mnth_yr, levels=

#Group by sales for each year
time_period_sales_group_by<- time_period_sales %>% group_by(order_date_mnth_yr)%>%summarise(

# Time series graph to show the quantity sold over a given time period

(ggplot(time_period_sales_group_by, aes(x = order_date_mnth_yr, y = quantity,group=1)) +  geo
```

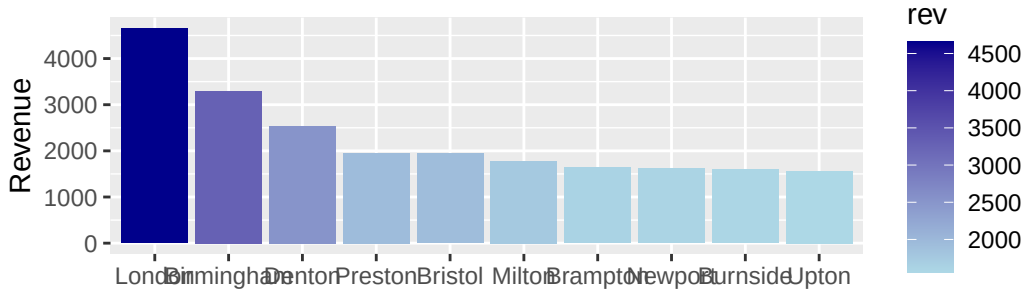



```
#Report 4:

#SQL query to join customer and order tables to get the sales for each city

cust_order_join<- RSQLite::dbGetQuery(connect, 'SELECT city,ORDITM.order_quantity FROM ADDRES

#cust_order_join<- inner_join(Customer,Order,by="customer_id")

#Grouping by city to get the overall sales per city

sales_per_region<- cust_order_join %>% group_by(city)%>%summarise(quantity=sum(order_quantity

#Get the top 10 cities for sales
top_10_sales_per_region <- sales_per_region[order(-sales_per_region$quantity),]

top_10_sales_per_region <- head(top_10_sales_per_region,10)

#Bar graph to show the sales per region

ggplot1 <- ggplot(top_10_sales_per_region, aes(x = reorder(city,-quantity), y = quantity,fill

#Table to get the revenue per city
```

```
cust_order_product_join <-RSQLite::dbGetQuery(connect, 'SELECT city,ORDITM.order_quantity,uni

#SQL Query to get the top 5 products

top_5_products <-RSQLite::dbGetQuery(connect, 'SELECT city,ORDITM.order_quantity,unit_price,

#Revenue calculation

cust_order_product_join$revenue <-  cust_order_product_join$order_quantity*cust_order_product

#Grouping by the get the revenue for each city
revenue_per_region <- cust_order_product_join %>% group_by(city) %>% summarise(rev= sum(rever

#Get the top 10 cities for revenue

top_5_revenue_per_region <- revenue_per_region[order(-revenue_per_region$rev),]

top_5_revenue_per_region <- head(top_5_revenue_per_region,10)

#Bar graph to show the revenue per region

ggplot2 <- ggplot(top_5_revenue_per_region, aes(x = reorder(city, -rev), y = rev,fill=rev)) +

grid.arrange(ggplot1,ggplot2)
```



Top 10 cities where sales is maximum



Top 10 cities with the maximum revenue

```
#revenue_per_product_region <- cust_order_product_join %>% group_by(city) %>% summarise(rev=

#Revenue calculation to show the top 5 products for each city with maximum revenue

top_5_products$revenue <- top_5_products$order_quantity*top_5_products$unit_price

top_5_products_region <- top_5_products %>% group_by(city,product_name) %>% summarise(rev= su
```

```
`summarise()` has grouped output by 'city'. You can override using the
`.groups` argument.
```

```
#Table to show the products that are sold for the top 2 revenue producing cities
(top_5_products_region <- top_5_products_region %>% filter(city %in% head(top_5_revenue_per_
```

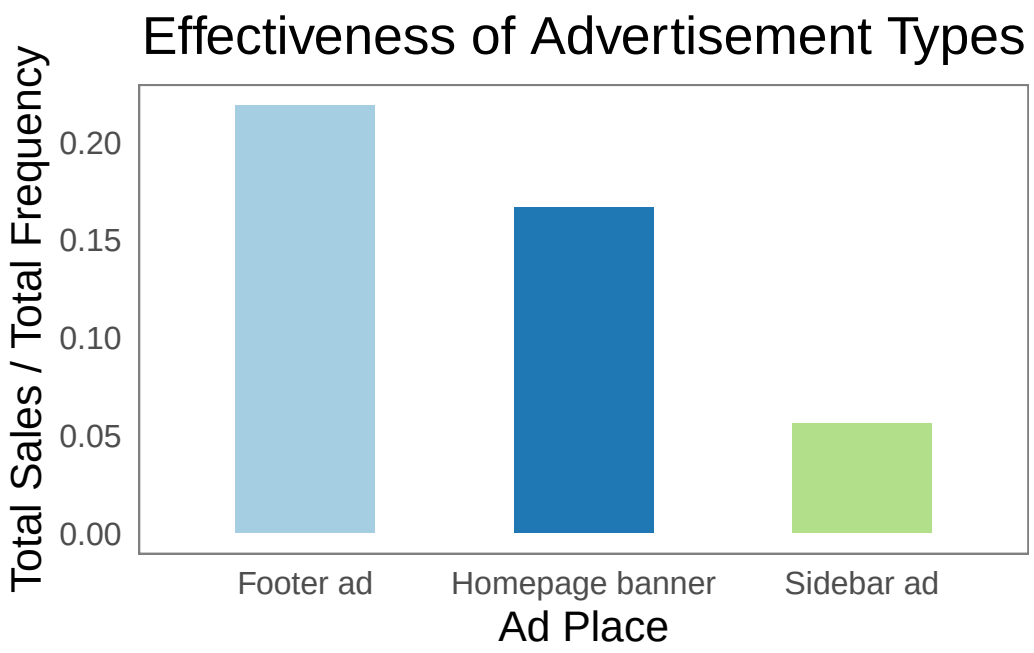
```
Adding missing grouping variables: `city`
```

```
# A tibble: 24 x 2
# Groups:   city [2]
   city       product_name
   <chr>      <chr>
 1 Birmingham Cosmic Compression Socks
```

```
 2 Birmingham Essence Room Diffuser
 3 Birmingham FusionX Gaming Console
 4 Birmingham Moonbeam Cardigan
 5 Birmingham Nebula Scarf
 6 Birmingham Solar Flare Sweater
 7 Birmingham Sonic Boom Portable Speaker
 8 Birmingham Sonic Boom Resistance Bands
 9 Birmingham Stellar Eyeshadow Palette
10 Birmingham Tranquility Scented Candles
# i 14 more rows
```

```
#Report 5
# Joining Product with advertise_in and advertisement to get advertisement details
advertise_in <- RSQLite::dbGetQuery(connect,'SELECT * FROM ADVERTISE_IN')
advertisement <- RSQLite::dbGetQuery(connect,'SELECT * FROM ADVERTISEMENT')

advertisement_data <- product %>%
  inner_join(advertise_in, by = "product_id") %>%
  inner_join(advertisement, by = "ad_id") %>%
  group_by(product_id, product_name, ad_place) %>%
  summarise(
    total_frequency = sum(ad_frequency), # Sum the total frequency of ads for each ad place
    .groups = 'drop' )


# Joining product with order to get the number of sales per product
number_of_sales <- product %>%
  inner_join(order_item, by = "product_id") %>%
  group_by(product_id, product_name) %>%
  summarise(sales_count = n(), .groups = 'drop')



merged_data <- merge(number_of_sales, advertisement_data, by = c("product_id", "product_name



# Analyzing which ad place is most effective by calculating a ratio of total sales to total a
effective_ad_type <- merged_data %>%
  group_by(ad_place) %>%
  summarise( total_sales = sum(sales_count),
             total_frequency = sum(total_frequency), .groups = 'drop') %>%
```

```
  mutate( effectiveness = total_sales / total_frequency) %>%
  arrange(desc(effectiveness))




ggplot(effective_ad_type, aes(x = ad_place, y = effectiveness, fill = ad_place)) +
  geom_col(show.legend = FALSE, width = 0.5) + # Adjust bar width here
  scale_fill_brewer(palette = "Paired") + # Use a more appealing color palette
  labs(title = "Effectiveness of Advertisement Types",
       x = "Ad Place",
       y = "Total Sales / Total Frequency") +
  theme_minimal(base_size = 14) + # Increase base text size for better readability
  theme(plot.title = element_text(hjust = 0.5, size = 20), # Center and style title
        axis.title = element_text(size = 16), # Style axis titles
        axis.text = element_text(size = 12), # Style axis texts
        panel.grid.major = element_blank(), # Remove major grid lines
        panel.grid.minor = element_blank(), # Remove minor grid lines
        panel.background = element_rect(fill = "white", colour = "grey50")) # Style panel ba
```




```
# #Report 6
# #Calculating Marketplace fee
```

```
# merged_product_fee <- product %>%
#   inner_join(select(category, category_id, category_fee, category_name), by = "category_id"
# category_fee <- order_item %>%
#   inner_join(select(order_detail, order_id, order_status), by = "order_id") %>%
#   inner_join(select(merged_product_fee, product_id, product_name, unit_price, category_fee
#   filter(order_status == "Completed") %>%
#   mutate(marketplace_fee = order_quantity * unit_price * category_fee/100) %>%
#   mutate(cat_total_sales = order_quantity * unit_price) %>%
#   group_by(category_id, category_name) %>%
#   summarise(total_fee = sum(marketplace_fee), total_sales = sum(cat_total_sales), total_sal
#
#
# #Visualise
#
#
# #Graph to compare Category sales VS Category Fee
# ggplot(category_fee, aes(x = reorder(category_name, -total_fee))) +
#   geom_bar(aes(y = total_sales, fill = "Total Sales"), stat = "identity", position = positi
#   geom_bar(aes(y = total_fee, fill = "Marketplace Fee"), stat = "identity", position = posi
#   scale_fill_manual(name = "Category", values = c("Marketplace Fee" = "#3182bd", "Total Sal
#   labs(title = "Marketplace Fee vs Total Sales by Category", x = "Category", y = "Amount, U
#   theme_minimal() +
#   theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
# #Report 7
# # Graph to compare Category sales VS Category average rating
# ggplot(category_fee, aes(x = reorder(category_name, -Average_Rating))) +
#   geom_bar(aes(y = total_sales_unit, fill = "Total Sales in Units"), stat = "identity", pos
#   geom_bar(aes(y = (Average_Rating-3)*20, fill = "Average Rating"), stat = "identity", posi
#   geom_text(aes(label = sprintf("%.2f", Average_Rating), y = Average_Rating, x = category_n
#             color = "black", size = 4, hjust = 0.5) +
#   scale_fill_manual(name = "Category", values = c("Average Rating" = "#FFCC80", "Total Sale
#   labs(title = "Average Rating vs Total Sales in Units by Category", x = "Category", y = "T
#   theme_minimal() +
#   theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
#   scale_y_continuous(name = "Total Sales in Units")
```

Task 4.2: Comprehensive Reporting with Quarto

Report 1: Profitability vs Popularity

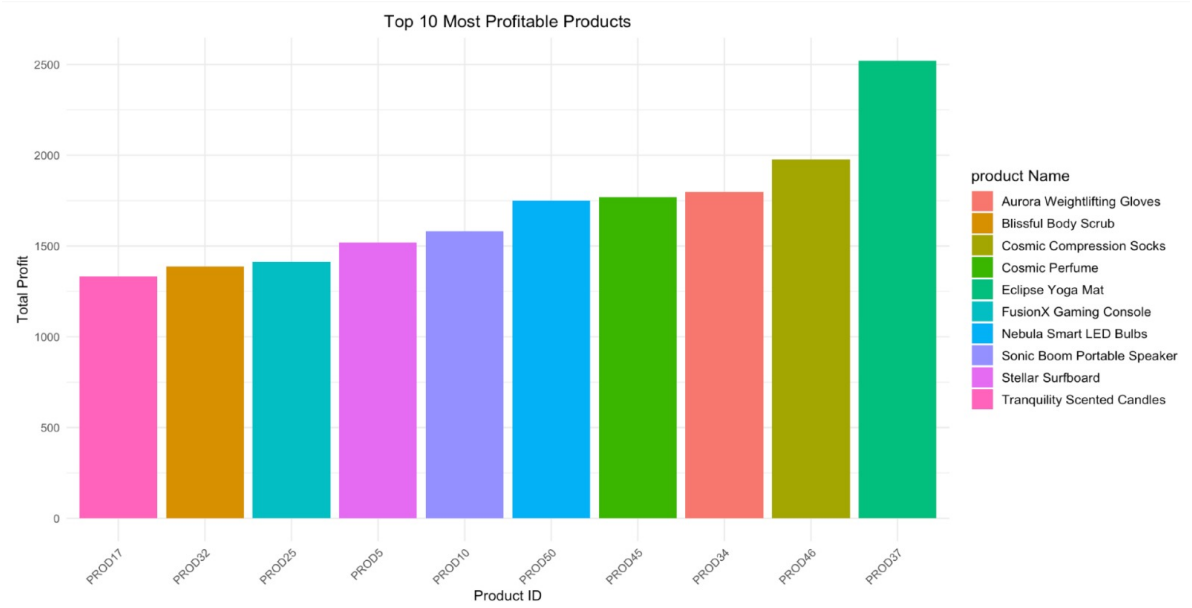


Figure 1: Figure 1

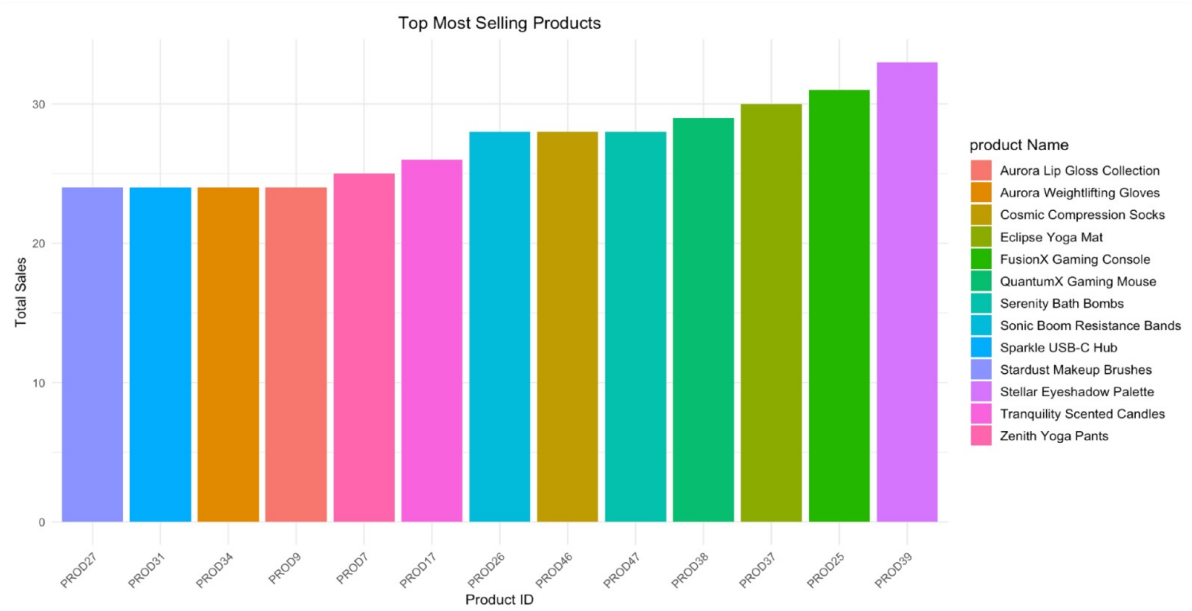


Figure 2: Figure 2

Figure 1 represents the profitability of individual products sold by the e-commerce company. The “Eclipse Yoga Mat” generates the highest profit for the company among the assortment.

This could indicate a higher margin or a premium pricing strategy. Conversely, Figure 2 illustrates sales volume, where items like the "Stellar Eyeshadow Palette" and "Fusion X Gaming Console" lead, suggesting they are favored choices among consumers.

Some products, including the "Aurora Weightlifting Gloves", "Cosmic Compression Socks" and "Tranquility Scented Candles," appear in both graphs, showcasing their strength in both popularity and profitability. This dual presence is indicative of a successful product strategy by the company. However, there are also noticeable discrepancies. For example, "QuantumX Gaming Mouse" appears as a top seller, yet it's absent from the most profitable items, implying a lower profit margin. In contrast, "Nebula Smart LED Bulbs" are among the most profitable but not the top sellers, suggesting a high margin compensating for lesser sales.

The e-commerce company could focus on marketing strategies for high-margin products to boost their volume of sales, thus increasing overall profitability. For products that sell well but are less profitable, the company may need to assess whether they can improve margins through better supplier negotiations.

Products that are both top sellers and highly profitable should be kept in optimum stock to avoid lost sales opportunities. For less profitable items, the company may consider keeping lower stock levels or even discontinuing them if they do not contribute significantly to overall profits.

Report 2: Bundled vs Individual Products

Table 1: *Table 1*

Product_Type	Total_Quantity_Sold
Bundled	491
Individual	499

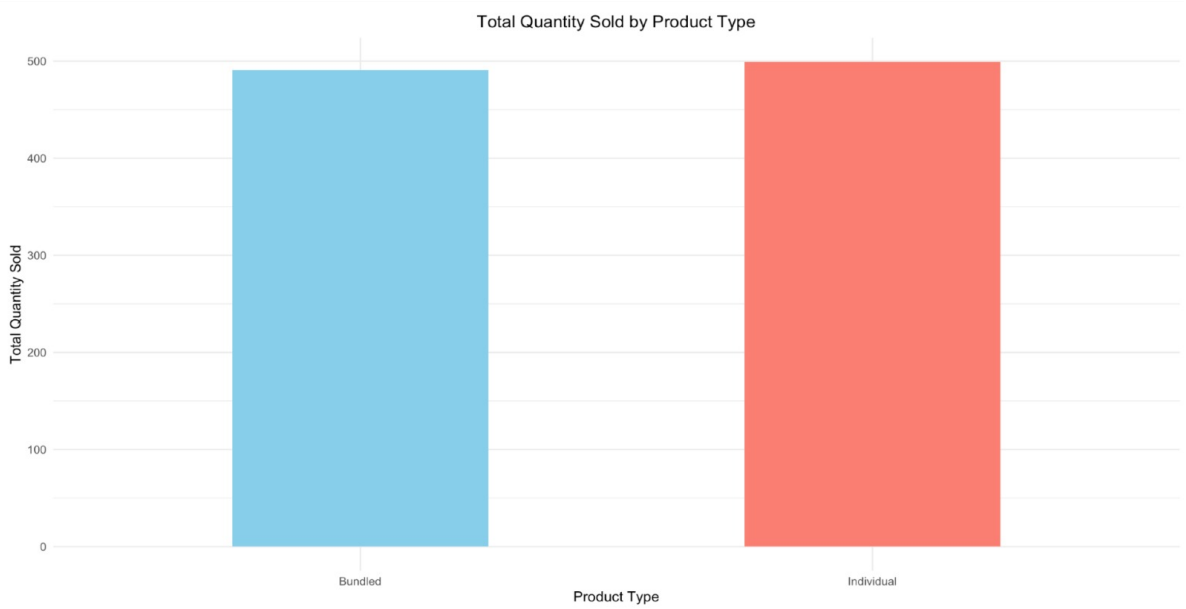


Figure 3: Figure 3

As seen in Table 1, the total sales for individual products (products sold without bundles) and bundled products yield nearly equal quantities sold. Individual products slightly outperform bundled products (499 vs 491). This suggests that the e-commerce company's bundling strategy to boost sales was not as effective as anticipated. However, it is difficult to conclude the efficacy of this deal based solely on the volume of sales.

Optimizing bundle offerings by analyzing and aligning them with customer preferences, based on the average product ratings, can significantly enhance their appeal. Experimenting with different bundle types and conducting a cost-benefit analysis might uncover ways to refine the strategy. The results (Figure 3) suggest a market demand for both types of products, indicating that customers prefer some flexibility in their buying options. Rather than discontinuing the bundle products, the company should look deeper into the performance metrics of this deal considering the inventory turnover and profit margins.

Report 3: Sales Trend over the given time period

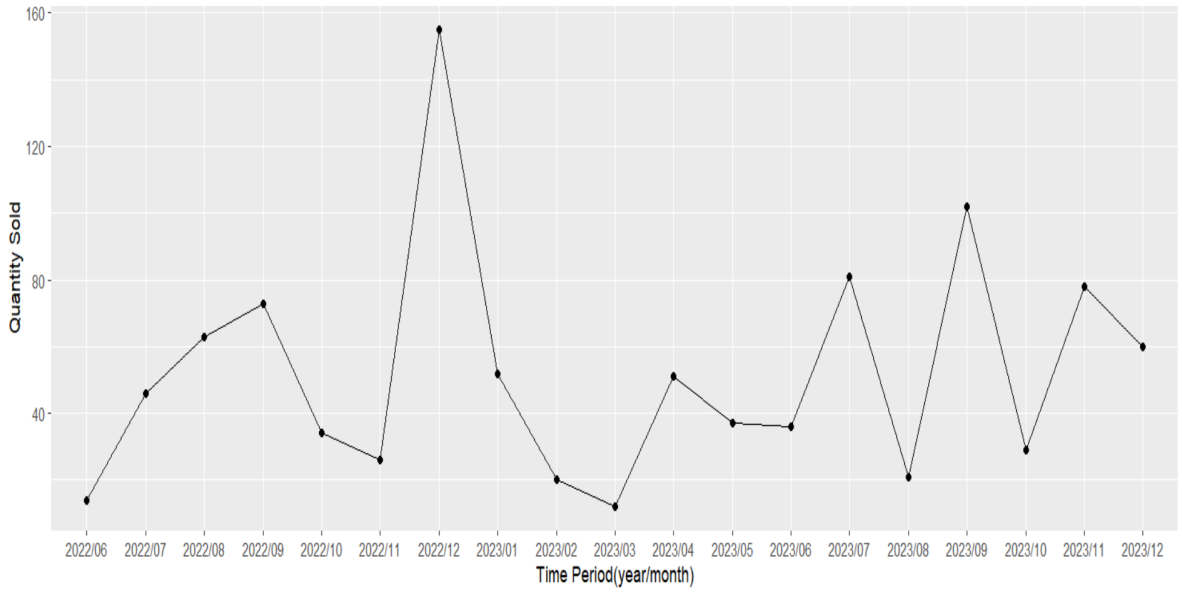


Figure 4: Time Series Graph to depict the seasonal trends in sales

Purchase pattern analysis is significant for an e-commerce company as different strategies could be deployed to maximize sales and revenue. Figure 4 illustrates that the sales was maximum at September and December months over the time-period from 2022 to 2023. Hence appropriate pricing strategies could be deployed to increase revenue from top selling products. Also, a sharp decline in sales is identified in October month which is later followed by an increase in succeeding months. This study could help in an efficient inventory management in place for perishable products. Overall, this variation in sales across different seasons provides important insights for better management decisions.

Report 4: Comparison of sales and revenue for each city

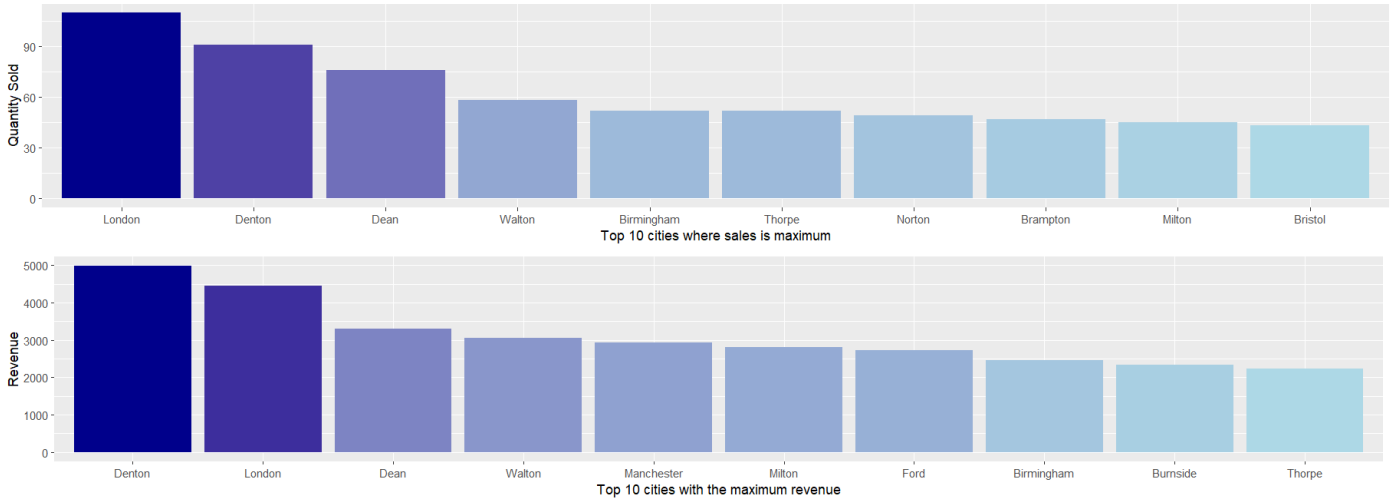


Figure 5: Top 10 cities with maximum revenue and sales

Figure 5 gives a crucial insight of cities that generated significant revenue with lesser quantity of products sold. Top Products from these cities could be identified as shown in table 1 as their sales could improvise revenue to a great extent. Also, cities like Ford, Manchester and Milton generated outstanding revenue even though their sales were limited.

Report 5: Analysis of Advertisement methods

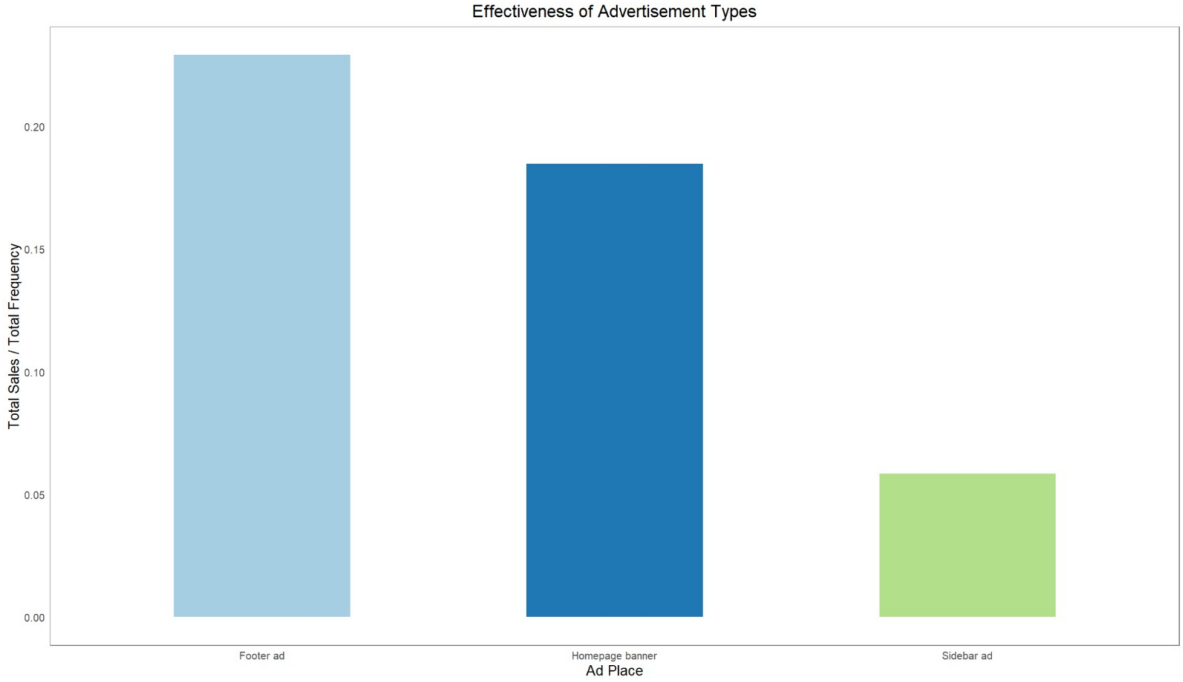


Figure 6: Sales of products per 1 advertisement of each type

We analysed 3 types of advertisements on the Marketplace to find that Products that are advertised with the Figure 6 shows that Footer ads on average have higher sales in units. The intention was to compare the number of units sold depending on the type of advertisement this product was in. This finding can be used to assign higher price for more efficient advertisement types to be charged from suppliers.

Report 6: Analysis of Marketplace transaction fees

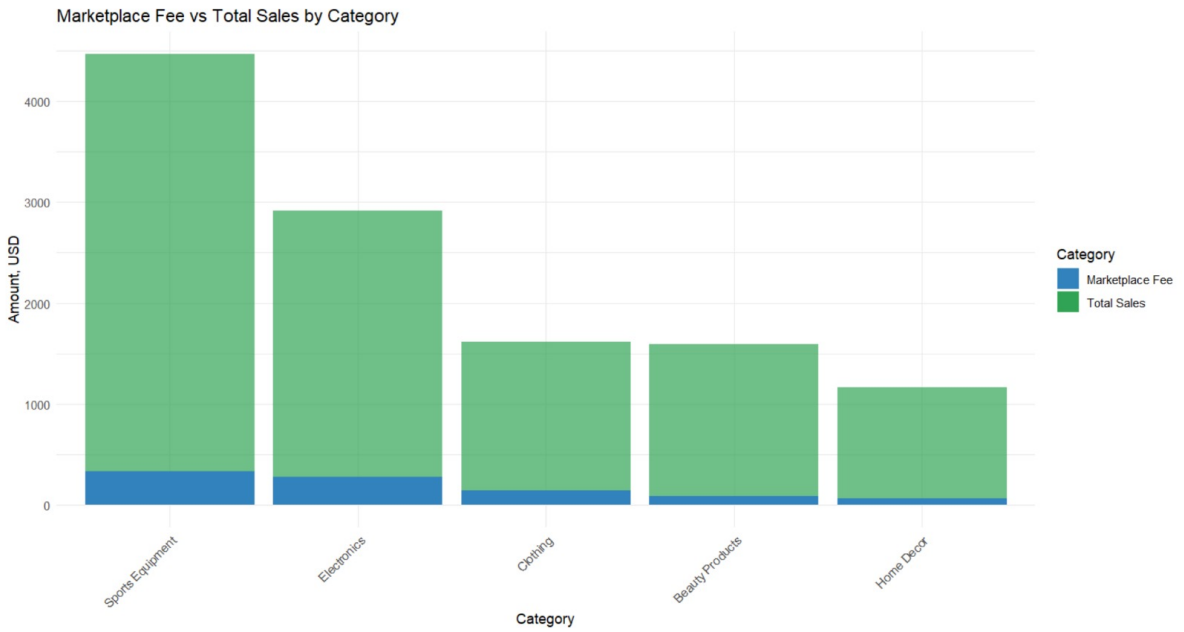


Figure 7: Comparing Marketplace fees to the sales in each Category of products

The marketplace is the mediator between the customer and seller, allowing convenience for both. This service is not free. Sellers pay fees for each transaction. These fees and advertisements make the marketplace profit. The fee varies depending on the category of goods. We compared the combined amount of fees for each sold item by category to find out which category brings the Marketplace more profit.

On Figure 7 we see that the higher the sales of the Category, the more fees Marketplace earns on it. We consider increasing fees for the categories with higher sales and decreasing fees for the categories with low sales to maximise Marketplace profit by selling more in less popular categories and getting higher fees for already popular ones. Sports Equipment has the highest sales in terms of money, however, as we will see later most units are sold in the Electronics category.

Report 7: Analysis of Customers reviews on sales for each category.

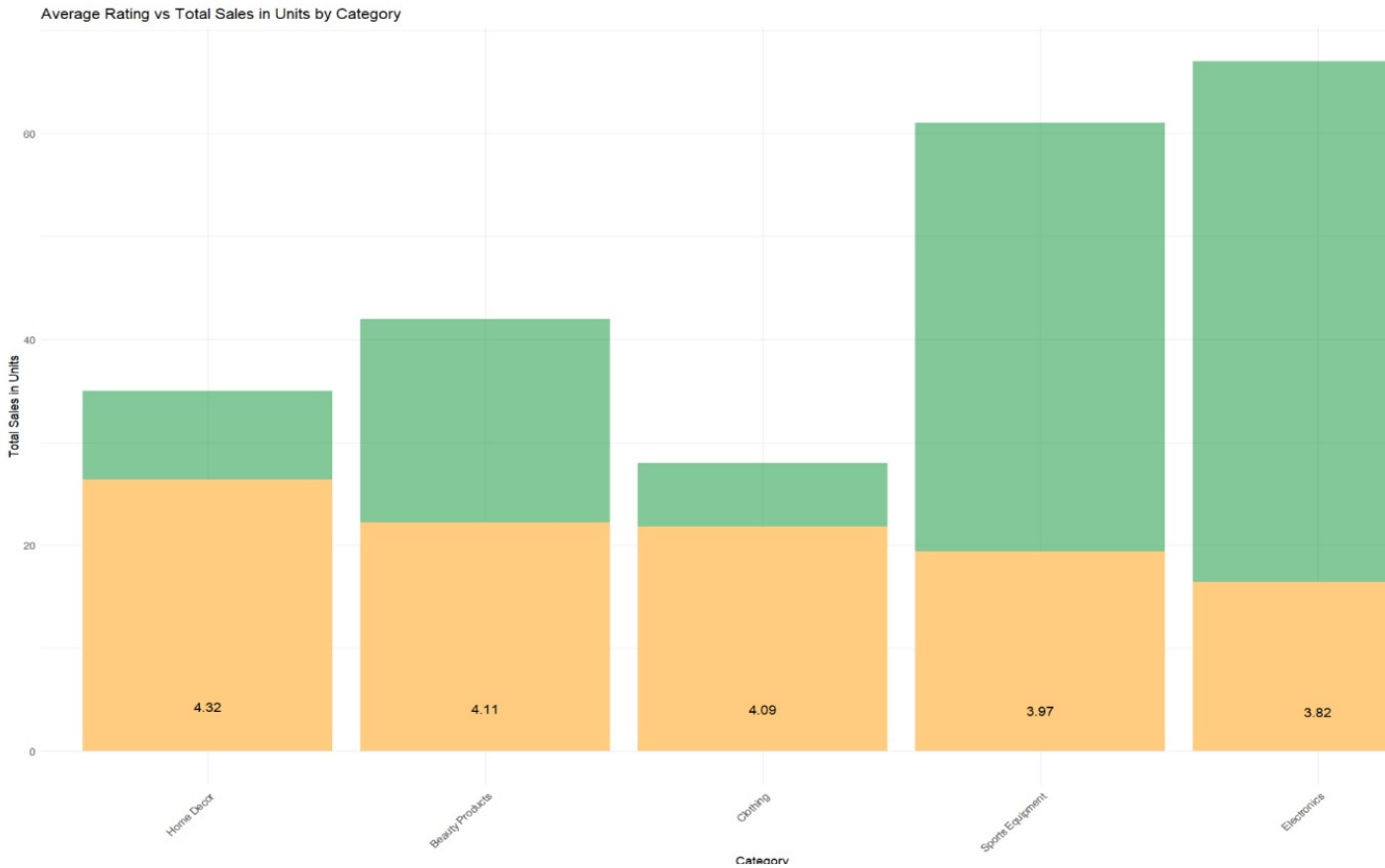


Figure 8: Average customers' rating for the category and category's sales in units

It was found that categories that have products with higher ratings have lower sales in units. This may appear wrong but most likely with the increase in sales the number of negative reviews increases at a higher rate. Marketplace may want to reconsider suppliers for the categories with lower average ratings.