Overview

The most crucial aspect of any thriving e-commerce business is the skilled management of data. Recognizing this, our project simulates a real-world e-commerce data environment, where our primary goal is to construct a robust database that can not only handle the high volume of transactions characteristic of busy online platforms but also organize data effectively to streamline operations. By recreating a realistic e-commerce scenario, we aim to ensure that businesses remain adaptable, perceptive, and ahead in the fast-paced world of e-commerce.

Part 1: Database Design and Implementation

1.1 E-R Diagram Design

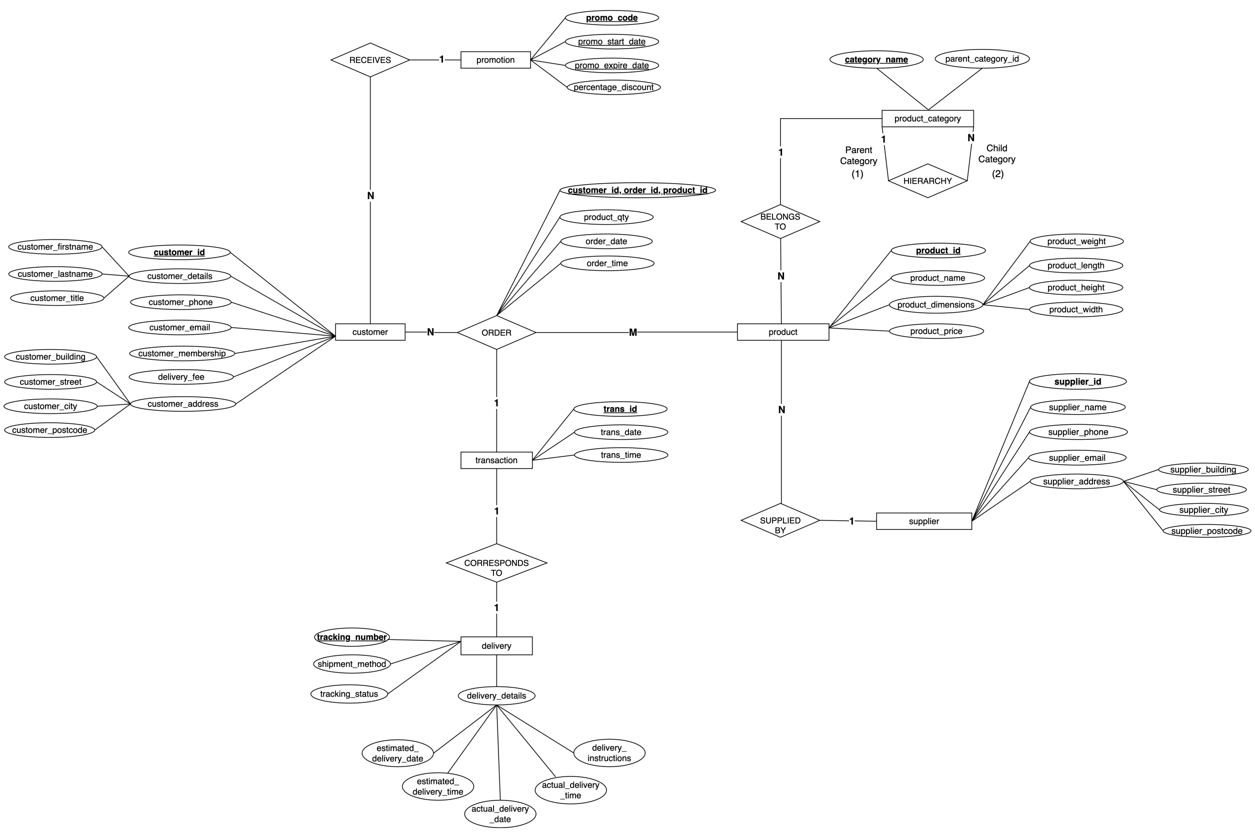


Figure 1: ER Diagram

The architecture of our e-commerce database is structured around seven key entities: customer, product, product category, supplier, promotion, transaction and delivery. We initially identified 12 entities, including review, return, cart, and advertisements, using an Excel spreadsheet (Appendix 5.1). However, identifying attributes, foreign keys and relationships proved challenging, especially in later SQL table creation stages. Therefore, we kept the seven most important to avoid any complexities. The final seven entities are intricately interconnected through a spectrum of relationships, including one-to-one, one-to-many, many-to-many, and self-referencing, in addition to a central ternary relationship. This comprehensive approach served as a roadmap guiding us through all subsequent stages of the database design.

The "customer" entity, uniquely identified by "customer_id", holds detailed attributes and forms a many-to-many relationship with "product" entity, signifying that customers can purchase multiple products, and products can be purchased by various customers.

The "product" entity has "product_id" as the primary key and is linked to "product category". It has a one-to-many relationship where one category can encompass numerous products. Furthermore, “product” is similarly linked with “supplier” entity that is uniquely identified by “supplier_id”. It is connected through a one-to-many relationship, under the assumption that one supplier provides numerous products.

The “product category” entity has a self-referencing relationship with “category_name” as the primary key. It is a hierarchical category structure with one-to-many relationship, as a single parent category can have multiple child categories, but each child category has only one parent category. For instance, “Beauty” is the parent category, and “Body Wash”, “Perfume” and “Hair Styling Product” are the child categories. Each of these child categories would refer to “Beauty” as their parent, creating a self-referencing relationship as is shown in figure 2.

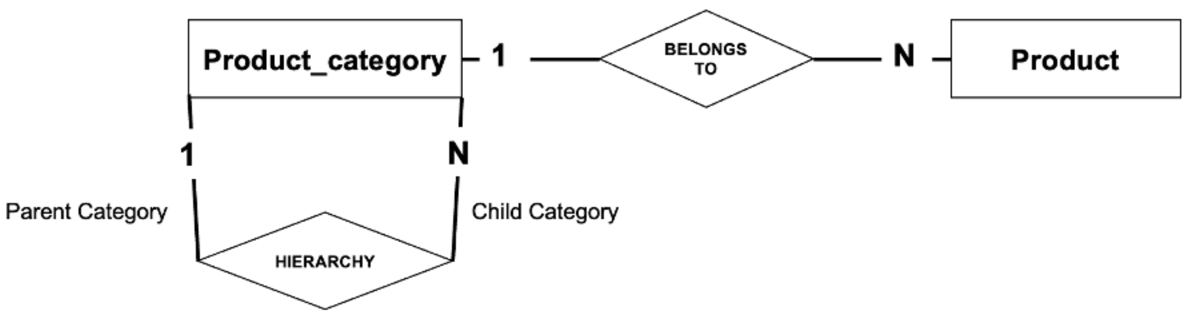


Figure 2. Self-Referencing Relationship

The “promotion” entity with “promo_code” as the primary key engages in a one-to-many relationship with “customer” entity, under the assumption that one customer can be associated with one promo code, and many promo code can be associated with multiple customers.

Central to the database, “transaction” captures the financial exchanges and is part of a ternary relationship with “customer” and “product” entities. The three are connected with “order” relationship as is shown below in figure 3:

- A “customer” can have multiple “transaction” (N:1), and within each transaction, multiple “products” can be involved (M:1).

- A “product” can be part of multiple “transaction” through different “customers” (M:N), but within a specific transaction, it is uniquely identified.

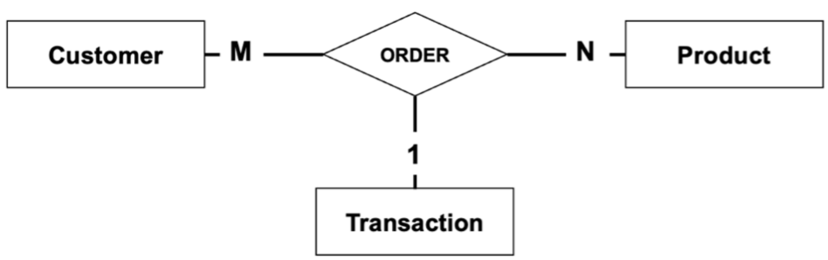
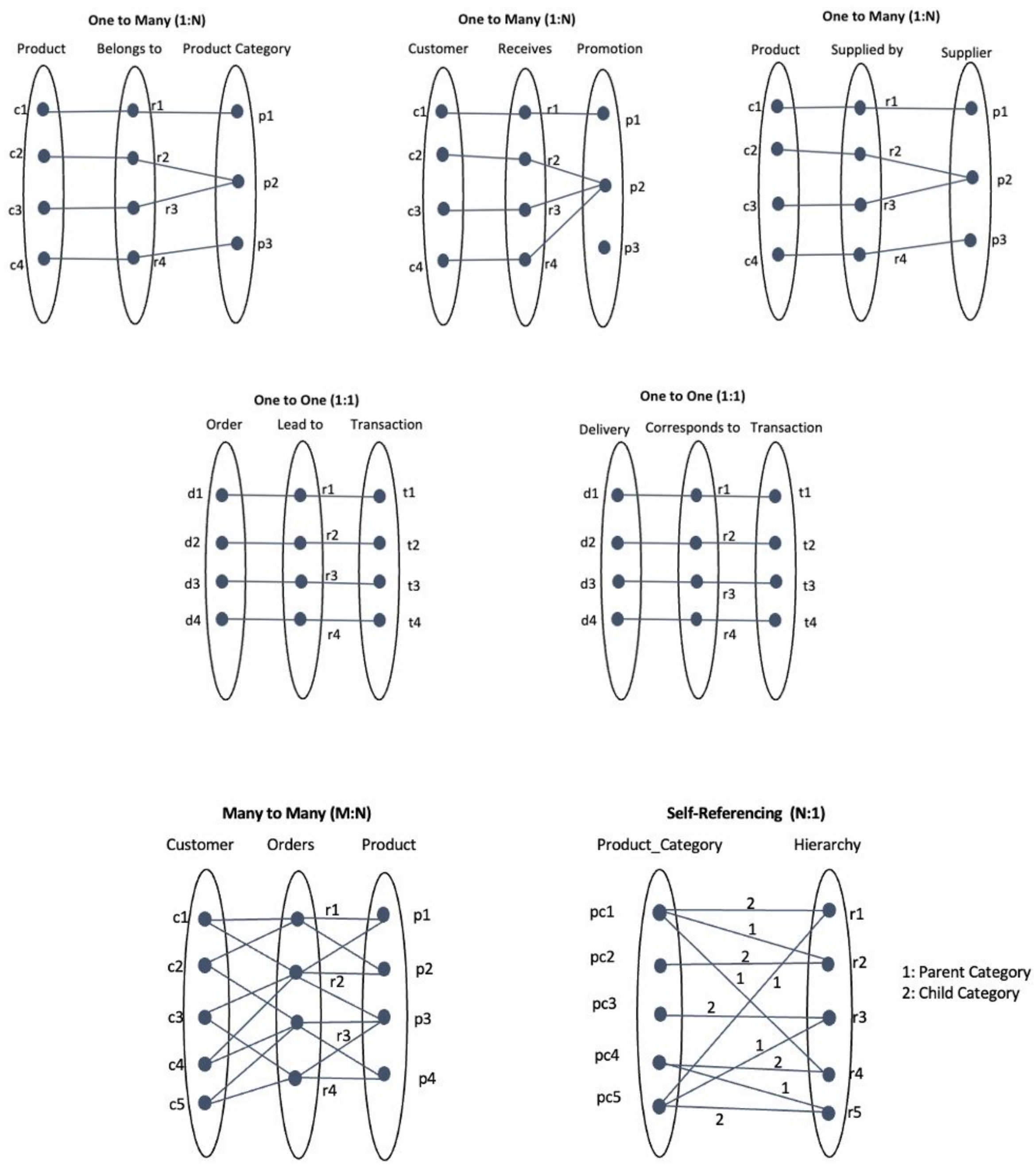


Figure 3. M:N:1 Ternary Relationship

Lastly, the “delivery” entity, with “delivery_id” as the primary key, correlates with “transaction” table in a one-to-one relationship, where each transaction results in a single delivery instance, ensuring that every purchase is accurately fulfilled.

All relationship sets are illustrated below based on each relationship between two entities:

Figure 4: Relationship Sets with Cardinality for an E-commerce Store



Assumptions

To shape our database's logical structure, we have established several assumptions. First, we assume that our E-commerce business commenced in June 2023. We have a singular supplier relationship where a product is supplied by only one supplier. Each customer and supplier have only one address within the United Kingdom, with every customer and supplier allowed to add only one email address and contact number. Furthermore, our operating procedure presumed that the recipient name for each order corresponds to the name provided by the customer during the ordering process. All product prices are listed in GBP, and a free delivery fee is applied to membership holders (shipment method such as express or next day will still be free). On the contrary, there's a delivery fee for customers without membership. All deliveries are handled by our own company, and not by an external company and all products within each order are shipped in one parcel. The delivery time is between 7am – 5pm, and each parcel is delivered to each customer's unique address. All transactions are considered as completed, with no pending or failed statuses, whereas orders placed prior to March 2024 are presumed to be delivered and completed. Lastly, membership fee is not considered as part of our revenue.

Logical Schema

Upon completion of the ER diagram, we moved to the logical schema phase where each attribute corresponds to a column within that table. Consequently, seven tables are established to represent the seven entities: product_category, promotion, supplier, customer, delivery, product and transaction.

When designing the logical schema, a careful review of entity relationships is crucial to determine if any additional tables are required. Relationships with cardinalities of 1:1 or N:1 do not require extra tables or changes. However, in N:1 relationships, where multiple instances of one entity are associated with a single instance of another, the primary key from the entity on the "1"- weak side transforms into a foreign key in the table on the "N" – strong side. In our ER diagram, we observe that multiple products belong to one product_category (N:1), and multiple products are supplied by one supplier (N:1). Thus, the primary keys "category_name" and "supplier_id" of the weak side are both transferred to the product table as foreign keys. This is the same case for "promo_code" from the promotion table transferred to the customer table as a foreign key. Below is a list of logical schemas for all entities:

1. Customer

customer (customer_id, promo_code, customer_firstname, customer_lastname, customer_title, customer_phone, customer_email, customer_membership, delivery_fee, customer_building, customer_street, customer_city, customer_postcode)

2. Delivery

delivery (tracking_number, trans_id, shipment_method, tracking_status, estimated_delivery_date, estimated_delivery_time, actual_delivery_date, actual_delivery_time, delivery_instructions)

3. Supplier

supplier (supplier_id, supplier_name, supplier_phone, supplier_email, supplier_building, supplier_street, supplier_city, supplier_postcode)

4. Transaction

transaction (trans_id, order_id, trans_date, trans_time)

5. Product category

product_category (category_name, parent_category_id)

6. Product

product (product_id, supplier_id, category_name, product_name, product_weight, product_length, product_height, product_width, product_price)

7. Promotion

promotion (promo_code, promo_start_date, promo_expire_date, percentage_discount)

Finally, due to the many-to-many (M:N) relationship between the customer and product tables, it is necessary to create an additional, separate table named 'order', which will contain additional attributes. The three attributes “order_id”, “customer_id” and “product_id” form a composite key that serves as a primary key for the “order” table, while “customer_id” and “product_id” also serve as a foreign key for the customer table and product table respectively.

8. Order

order (order_id , customer_id, product_id, product_qty, order_date, order_time)

Part 1.2: Database Schema Creation

The database schema creation process starts with establishing a connection and creating SQL tables for each entity, proactively dropping any pre-existing tables to avoid potential issues. Then we used the 'CREATE TABLE' statements to define the new tables within the database. Each table corresponds to an entity in the E-commerce system, which defines the corresponding attributes, data types, null or not null and foreign-primary keys. Also, we meticulously ensured that all tables are aligned with our conceptual and logical schema.

Load Files in an sqlite database

```r
# setup the connection
connection <- RSQLite::dbConnect(RSQLite::SQLite(), "hi_import.db")
```

Drop tables

```sql
DROP TABLE IF EXISTS product
```

```sql
DROP TABLE IF EXISTS product_category
```

```sql
DROP TABLE IF EXISTS promotion
```

```sql
DROP TABLE IF EXISTS supplier
```

```sql
DROP TABLE IF EXISTS "transaction"
```

```sql
DROP TABLE IF EXISTS order_datetime
```

```sql
DROP TABLE IF EXISTS order_products_info
```

```sql
DROP TABLE IF EXISTS actual_delivery_date
```

```sql
DROP TABLE IF EXISTS delivery_tracking
```

```sql
DROP TABLE IF EXISTS estimated_delivery_date
```

```sql
DROP TABLE IF EXISTS customer_membership
```

```sql
DROP TABLE IF EXISTS customer_basic_info
```

```sql
DROP TABLE IF EXISTS customer
```

```sql
DROP TABLE IF EXISTS delivery
```

```sql
DROP TABLE IF EXISTS "order"
```

Create SQL tables

product_category

```sql
-- product_category
CREATE TABLE "product_category" (
  category_name VARCHAR(50) PRIMARY KEY,
  parent_category_id CHAR NULL
);
```

```sql
SELECT * FROM "product_category";
```

Table 1: 0 records

category_name	parent_category_id

promotion

```sql
-- promotion
CREATE TABLE "promotion" (
  promo_code INT PRIMARY KEY,
  promo_start_date DATE NULL,
  promo_expire_date DATE NULL,
  percentage_discount NUMERIC NOT NULL
  );
```

```sql
SELECT * FROM "promotion";
```

Table 2: 0 records

promo_code	promo_start_date	promo_expire_date	percentage_discount

supplier

```sql
-- supplier
CREATE TABLE supplier (
  supplier_id INT PRIMARY KEY,
  supplier_name CHAR NOT NULL,
  supplier_phone INT NOT NULL,
  supplier_email VARCHAR(50) NOT NULL,
  supplier_building INT NOT NULL,
  supplier_street VARCHAR(50) NOT NULL,
  supplier_city VARCHAR(50) NOT NULL,
  supplier_postcode VARCHAR(50) NOT NULL
) ;
```

```sql
SELECT * FROM "supplier";
```

Table 3: 0 records

supplier_id	supplier_name	supplier_phone	supplier_email	supplier_building	supplier_street	supplier_city	supplier_postcode

customer

```sql
-- customer
CREATE TABLE "customer" (
  customer_id INT PRIMARY KEY,
  promo_code INT,
  customer_firstname VARCHAR(50) NOT NULL,
  customer_lastname VARCHAR(50) NOT NULL,
```

```sql
  customer_title VARCHAR(25) NOT NULL,
  customer_phone VARCHAR(50) NOT NULL,
  customer_email VARCHAR(50) NOT NULL,
  customer_membership TEXT NOT NULL,
  delivery_fee NUMERIC NOT NULL,
  customer_building INT NOT NULL,
  customer_street VARCHAR(50) NOT NULL,
  customer_city VARCHAR(50) NOT NULL,
  customer_postcode VARCHAR(50) NOT NULL,
  FOREIGN KEY (promo_code) REFERENCES "promotion"(promo_code)
) ;
```

```sql
SELECT * FROM "customer";
```

Table 4: 0 records

customer_id	promo_code	customer_firstname	customer_lastname	customer_title	customer_phone	customer_email	customer_membership	delivery_fee	customer_building	customer_street	customer_city	customer_postcode

delivery

```sql
-- delivery
CREATE TABLE "delivery" (
  tracking_number INT PRIMARY KEY,
  trans_id INT,
  shipment_method VARCHAR(50) NOT NULL,
  tracking_status VARCHAR(50) NOT NULL,
  estimated_delivery_date DATE NOT NULL,
  estimated_delivery_time TIME NOT NULL,
  actual_delivery_date DATE NULL,
  actual_delivery_time TIME NULL,
  delivery_instructions VARCHAR(125) NOT NULL,
  FOREIGN KEY (trans_id) REFERENCES "transaction"(trans_id)
);
```

```sql
SELECT * FROM "delivery";
```

Table 5: 0 records

tracking_number	trans_id	shipment_method	tracking_status	estimated_delivery_date	estimated_delivery_time	actual_delivery_date	actual_delivery_time	delivery_instructions

product

```sql
-- product
CREATE TABLE "product" (
  product_id INT PRIMARY KEY,
  supplier_id INT,
  category_name VARCHAR(50),
  product_name VARCHAR(25) NOT NULL,
  product_weight NUMERIC NOT NULL,
  product_length NUMERIC NOT NULL,
  product_height NUMERIC NOT NULL,
```

```
  product_width NUMERIC NOT NULL,
  product_price NUMERIC NOT NULL,
  FOREIGN KEY (supplier_id) REFERENCES "supplier"(supplier_id),
  FOREIGN KEY (category_name) REFERENCES "product_category"(category_name)
) ;
```

```
SELECT * FROM "product";
```

Table 6: 0 records

product_id	supplier_id	category_name	product_name	product_weight	product_length	product_height	product_width	product_price

order

```
-- order
CREATE TABLE "order" (
  order_id INT,
  customer_id INT,
  product_id INT,
  product_qty INT NOT NULL,
  order_date DATE NOT NULL,
  order_time TIME NOT NULL,
  PRIMARY KEY (order_id, customer_id, product_id),
  FOREIGN KEY (customer_id) REFERENCES "customer"(customer_id),
  FOREIGN KEY (product_id) REFERENCES "product"(product_id)
) ;
```

```
SELECT * FROM "order";
```

Table 7: 0 records

order_id	customer_id	product_id	product_qty	order_date	order_time

transaction

```
-- transaction
CREATE TABLE "transaction" (
  trans_id INT PRIMARY KEY,
  order_id INT,
  trans_date DATE NOT NULL,
  trans_time TIME NOT NULL,
  FOREIGN KEY (order_id) REFERENCES "order"(order_id)
);
```

```
SELECT * FROM "transaction";
```

Table 8: 0 records

trans_id	order_id	trans_date	trans_time

Normalization to 3NF

Next, we ensured data integrity by checking for normalization before importing the dataset into the database. Our group chose to generate the data before creating the empty tables in SQL. This approach facilitated the verification of whether all tables were normalized up to the Third Normal Form (3NF), ensuring optimal data organization and integrity.

Therefore, before importing the synthetic dataset, we checked if our tables were in the First Normal Form (1NF), which required atomic values. For instance, the "customer_address" attribute in the customer table required us to separate columns for "customer_building", "customer_street", and "customer_city", ensuring each contained only a singular value. We then ensured compliance with the Second Normal Form (2NF) by ensuring all columns in all tables were only dependent on the primary keys and not any non-key attributes. For example, in transaction table, we computed the transaction amount by considering delivery fee, discount, quantity and products price. However, this calculation violated 2NF normalization principles and thus, we introduced a calculated field in SQL to handle this computation as it shown in the code after data validation and import.

Next, in achieving 3NF, we divided the customer table into two: customer_basic_info for personal details, and customer_membership for membership and fees, correcting a transitive dependency where 'delivery_fee' relied on 'customer_membership', not the 'customer_id' primary key.

A similar approach was taken with the order table, where the composite key of "order_id", "customer_id", and "product_id" is the primary key. Since "order_date" and "order_time" were fully dependent only on "order_id" and "customer_id", we segregated this information into a new table, order_datetime and order_products_info, thus removing the transitive dependency and aligning with 3NF principles.

The delivery table was split into estimated_delivery_date, actual_delivery_date, and delivery_tracking to meet 3NF. The estimated_delivery_date table now separately records shipment methods with estimated times, resolving a transitive dependency. The actual_delivery_date table captures timestamps based on "tracking_status", and the delivery_tracking table aligns `trans_id` and instructions with the `tracking_number` key.

For customer

1. customer_basic_info

```sql
-- customer_basic_info
CREATE TABLE "customer_basic_info" (
  customer_id INT PRIMARY KEY,
  promo_code INT,
  customer_firstname VARCHAR(50) NOT NULL,
  customer_lastname VARCHAR(50) NOT NULL,
  customer_title VARCHAR(25) NOT NULL,
  customer_phone VARCHAR(50) NOT NULL,
  customer_email VARCHAR(50) NOT NULL,
  customer_building INT NOT NULL,
  customer_street VARCHAR(50) NOT NULL,
  customer_city VARCHAR(50) NOT NULL,
  customer_postcode VARCHAR(50) NOT NULL,
  FOREIGN KEY (promo_code) REFERENCES "promotion"(promo_code)
) ;
```

```sql
SELECT * FROM customer_basic_info
```

Table 9: 0 records

customer_id	promo_code	customer_firstname	customer_lastname	customer_title	customer_phone	customer_email	customer_building	customer_street	customer_city	customer_postcode

2. customer_membership

```
-- customer_membership
CREATE TABLE "customer_membership" (
  customer_id INT,
  customer_membership TEXT,
  delivery_fee NUMERIC NOT NULL,
  PRIMARY KEY (customer_id, customer_membership),
  FOREIGN KEY (customer_id) REFERENCES "customer_basic_info"(customer_id)
);
```

```
SELECT * FROM customer_membership
```

Table 10: 0 records

customer_id	customer_membership	delivery_fee

For order

1. order_products_info

```
-- order_products_info
CREATE TABLE "order_products_info" (
  order_id INT,
  customer_id INT,
  product_id INT,
  product_qty INT NOT NULL,
  PRIMARY KEY (order_id, customer_id, product_id),
  FOREIGN KEY (customer_id) REFERENCES "customer_basic_info"(customer_id),
  FOREIGN KEY (product_id) REFERENCES "product"(product_id)
) ;
```

```
SELECT * FROM order_products_info
```

Table 11: 0 records

order_id	customer_id	product_id	product_qty

2. order_datetime

```
-- order_datetime
CREATE TABLE "order_datetime" (
  order_id INT,
  customer_id INT,
  order_date DATE NOT NULL,
  order_time TIME NOT NULL,
  PRIMARY KEY (order_id, customer_id),
  FOREIGN KEY (customer_id) REFERENCES "customer_basic_info"(customer_id)
) ;
```

```sql
SELECT * FROM order_datetime
```

Table 12: 0 records

order_id	customer_id	order_date	order_time

For Delivery

1. delivery_tracking

```sql
-- delivery_tracking
CREATE TABLE "delivery_tracking" (
  tracking_number INT PRIMARY KEY,
  trans_id INT,
  delivery_instructions VARCHAR(125) NOT NULL,
  FOREIGN KEY (trans_id) REFERENCES "transaction"(trans_id)
);
```

```sql
SELECT * FROM delivery_tracking
```

Table 13: 0 records

tracking_number	trans_id	delivery_instructions

2. estimated_delivery_date

```sql
-- estimated_delivery_date
CREATE TABLE "estimated_delivery_date" (
  tracking_number INT,
  shipment_method VARCHAR(50),
  estimated_delivery_date DATE NOT NULL,
  estimated_delivery_time TIME NOT NULL,
  PRIMARY KEY (tracking_number, shipment_method),
  FOREIGN KEY (tracking_number) REFERENCES "delivery_tracking"(tracking_number)
);
```

```sql
SELECT * FROM estimated_delivery_date
```

Table 14: 0 records

tracking_number	shipment_method	estimated_delivery_date	estimated_delivery_time

3. actual_delivery_date

```sql
-- actual_delivery_date
CREATE TABLE "actual_delivery_date" (
  tracking_number INT,
  tracking_status VARCHAR(50),
  actual_delivery_date DATE NULL,
  actual_delivery_time TIME NULL,
  PRIMARY KEY (tracking_number, tracking_status),
  FOREIGN KEY (tracking_number) REFERENCES "delivery_tracking"(tracking_number)
);
```

```sql
SELECT * FROM actual_delivery_date
```

Table 15: 0 records

tracking_number	tracking_status	actual_delivery_date	actual_delivery_time

The revised ER Normalized Diagram with the new entities of estimated_delivery_date, actual_delivery_date, delivery tracking, order_products info, order_datetime, customer_basic_info and customer_membership is presented in figure 5.

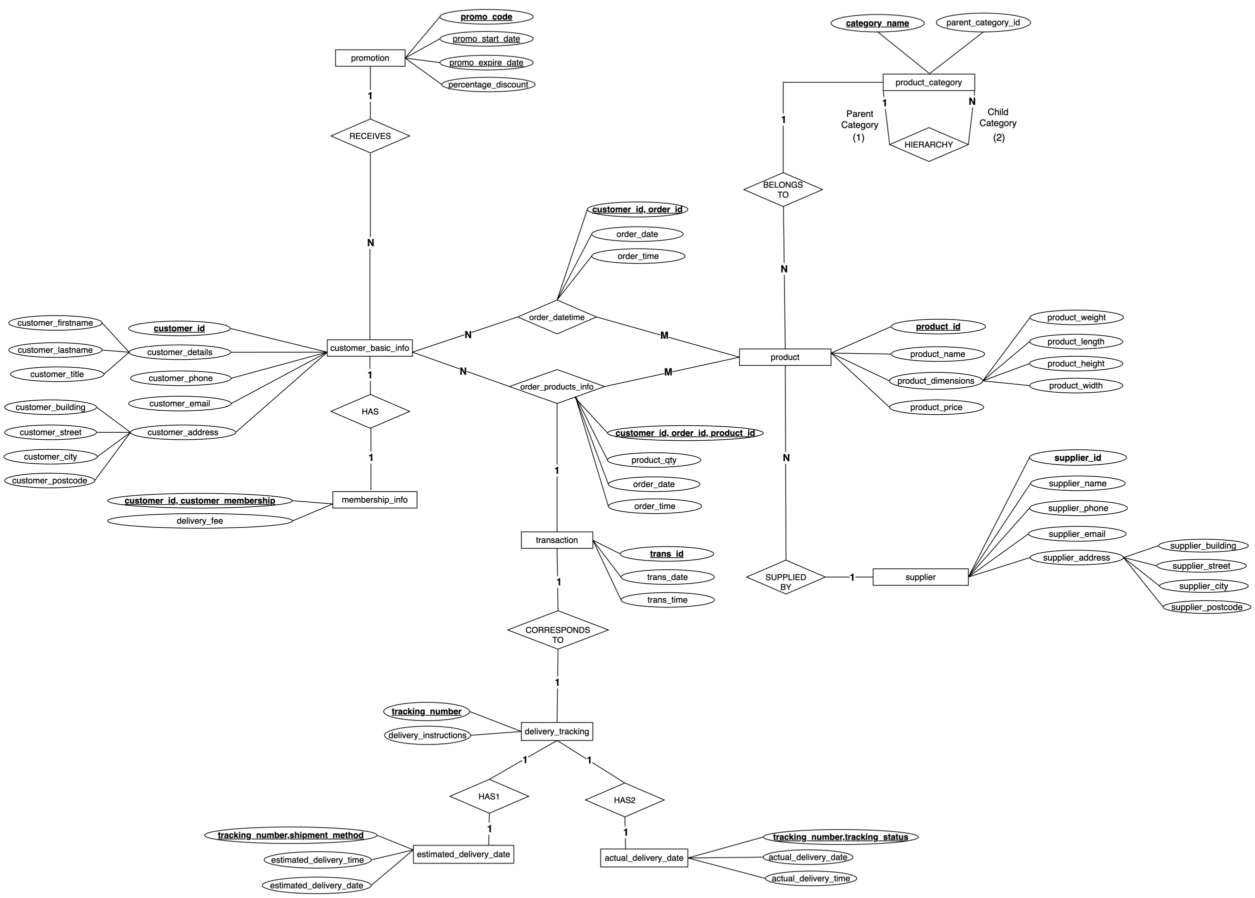


Figure 5: ER Diagram - After Normalisation

Part 2: Data Generation and Management

Part 2.1: Synthetic Data Generation

We initially generated synthetic data using Mockaroo and ChatGPT, which was downloaded into an excel sheet by providing field names, data types, and other conditions. However, we faced various issues including the fact that the total number of products was equally distributed in each category. There was also inconsistency in the address for various customers and thus, we had to go back and provide more information to get the desired results. In addition, there was one main issue with this data, including improper format and unordered date and time across promotion, order, transaction and delivery table. To correct this issue, we used R to re-generate this data for all related tables with conditions to ensure that promotion code is applicable during operation period (Appendix 5.2). We changed date and time data since they should follow a synchronized order: a customer places an order by making a transaction and then we have the date and time when the order is delivered. In addition, for delivery table, we also generated the estimated and actual delivery date based on the condition of shipment method.

Part 2.2: Data Quality Assurance and Import

Data Validation

In our pursuit of ensuring data integrity, we implemented a comprehensive quality assurance process which included:

1. Verification of the total number of rows and columns.
2. Data structure and formats.
3. Null values.
4. Validation of primary keys.
5. Validate phone number
6. Validate email address

By using a "for loop", we are able to perform these checks across all columns in each table. Each dataset should be verified to have unique value for primary key and no missing value for fields which required to have information. However, for Order dataset, there are some unique requirements as we have component primary key, we have created different process to handle this scenario. Furthermore, in Customer dataset, there are e-mail and phone number columns, which required specific format checks. For e-mail, special characters "@" and ending domain must be validated. For phone number, IT must be ensured to have 10 numeric characters.

List all files

```r
all_files <- list.files("Dataset/")
all_files
```

```
##  [1] "hi_actual_delivery_date_dataset.csv"
##  [2] "hi_customer_basic_info_dataset.csv"
##  [3] "hi_customer_membership_dataset.csv"
##  [4] "hi_delivery_tracking_dataset.csv"
##  [5] "hi_estimated_delivery_date_dataset.csv"
##  [6] "hi_order_datetime_dataset.csv"
##  [7] "hi_order_products_info_dataset.csv"
##  [8] "hi_product_category_dataset.csv"
##  [9] "hi_product_dataset.csv"
## [10] "hi_promotion_dataset.csv"
## [11] "hi_supplier_dataset.csv"
## [12] "hi_transaction_dataset.csv"
```

```r
prefix <- "hi_"
suffix <- "_dataset.csv"
all_files <- gsub("hi_", "", all_files)
all_files <- gsub("_dataset.csv", "", all_files)
all_files
```

```
##  [1] "actual_delivery_date"    "customer_basic_info"
##  [3] "customer_membership"     "delivery_tracking"
##  [5] "estimated_delivery_date" "order_datetime"
##  [7] "order_products_info"     "product_category"
##  [9] "product"                 "promotion"
## [11] "supplier"                "transaction"
```

In our pursuit of ensuring data integrity, we implemented a comprehensive quality assurance process which included:

1. Check number of rows and columns

```r
all_files <- list.files("Dataset/")

for (variable in all_files) {
    this_filepath <- paste0("Dataset/", variable)
    this_file_contents <- readr::read_csv(this_filepath)

    number_of_rows <- nrow(this_file_contents)
    number_of_columns <- ncol(this_file_contents)

    print(paste0("The file: ", variable, " has: ", format(number_of_rows,
        big.mark = ","), " rows and ", number_of_columns, " columns"))
}
```

```
## [1] "The file: hi_actual_delivery_date_dataset.csv has: 1,000 rows and 4 columns"
## [1] "The file: hi_customer_basic_info_dataset.csv has: 1,000 rows and 11 columns"
## [1] "The file: hi_customer_membership_dataset.csv has: 1,000 rows and 3 columns"
## [1] "The file: hi_delivery_tracking_dataset.csv has: 1,000 rows and 3 columns"
## [1] "The file: hi_estimated_delivery_date_dataset.csv has: 1,000 rows and 4 columns"
## [1] "The file: hi_order_datetime_dataset.csv has: 1,681 rows and 4 columns"
## [1] "The file: hi_order_products_info_dataset.csv has: 3,401 rows and 4 columns"
## [1] "The file: hi_product_category_dataset.csv has: 88 rows and 2 columns"
## [1] "The file: hi_product_dataset.csv has: 1,000 rows and 9 columns"
## [1] "The file: hi_promotion_dataset.csv has: 1,000 rows and 4 columns"
## [1] "The file: hi_supplier_dataset.csv has: 1,000 rows and 8 columns"
## [1] "The file: hi_transaction_dataset.csv has: 1,000 rows and 4 columns"
```

2. Check the data structure

```r
all_files <- list.files("Dataset/")

for (variable in all_files) {
    this_filepath <- paste0("Dataset/", variable)
    this_file_contents <- readr::read_csv(this_filepath)
    data_structure <- str(this_file_contents)

    print(paste0(data_structure, "The file: ", variable, " has above data structure"))
}
```

```
## spc_tbl_ [1,000 x 4] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ tracking_number     : chr [1:1000] "581-6200" "004-1482" "064-9023" "657-4120" ...
##  $ tracking_status     : chr [1:1000] "Delivered" "Delivered" "In process" "Delivered" ...
##  $ actual_delivery_date: Date[1:1000], format: "2023-06-24" "2023-11-22" ...
##  $ actual_delivery_time: 'hms' num [1:1000] 12:45:44 08:18:48 NA 07:43:05 ...
##   ..- attr(*, "units")= chr "secs"
##  - attr(*, "spec")=
##   .. cols(
##   ..   tracking_number = col_character(),
##   ..   tracking_status = col_character(),
##   ..   actual_delivery_date = col_date(format = ""),
```

```
##   ..   actual_delivery_time = col_time(format = "")
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_actual_delivery_date_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 11] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ customer_id       : chr [1:1000] "NAT-21446" "MQV-12400" "MLY-44705" "RFE-59474" ...
##  $ customer_firstname: chr [1:1000] "Mike" "Antone" "Moria" "Ichabod" ...
##  $ customer_lastname : chr [1:1000] "Berriball" "Lujan" "Llewellen" "Philson" ...
##  $ customer_title    : chr [1:1000] "Dr" "Mr" "Honorable" "Honorable" ...
##  $ customer_phone    : chr [1:1000] "+44 482 422 6609" "+44 941 356 9889" "+44 398 412 8484" "+44 114
##  $ customer_email    : chr [1:1000] "mberriball0@abc.net.au" "alujan1@qq.com" "mllewellen2@hud.gov"
##  $ customer_building : num [1:1000] 103 436 861 271 107 72 701 21 615 122 ...
##  $ customer_street   : chr [1:1000] "Willow Street" "Spruce Street" "Willow Street" "Maple Street" .
##  $ customer_city     : chr [1:1000] "Birmingham" "Birmingham" "Bristol" "Bristol" ...
##  $ customer_postcode : chr [1:1000] "B1D 6RT" "G1A 8DD" "G4H 0NH" "M04 5UF" ...
##  $ promo_code        : chr [1:1000] "VS04A935ONO" "OQ50R170HWT" "DU63L727XKV" "IW96D852NGT" ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   customer_id = col_character(),
##   ..   customer_firstname = col_character(),
##   ..   customer_lastname = col_character(),
##   ..   customer_title = col_character(),
##   ..   customer_phone = col_character(),
##   ..   customer_email = col_character(),
##   ..   customer_building = col_double(),
##   ..   customer_street = col_character(),
##   ..   customer_city = col_character(),
##   ..   customer_postcode = col_character(),
##   ..   promo_code = col_character()
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_customer_basic_info_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 3] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ customer_id        : chr [1:1000] "NAT-21446" "MQV-12400" "MLY-44705" "RFE-59474" ...
##  $ customer_membership: chr [1:1000] "membership" "not membership" "not membership" "membership" ...
##  $ delivery_fee       : num [1:1000] 0 4.99 5.99 0 0 2.99 5.99 0 6.99 5.99 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   customer_id = col_character(),
##   ..   customer_membership = col_character(),
##   ..   delivery_fee = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_customer_membership_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 3] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ tracking_number      : chr [1:1000] "581-6200" "004-1482" "064-9023" "657-4120" ...
##  $ delivery_instructions: chr [1:1000] "ring bell" "delivery box" "ring bell" "leave infront of door
##  $ trans_id             : chr [1:1000] "AAA-067232" "AAC-152328" "AAD-850184" "AAR-680860" ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   tracking_number = col_character(),
##   ..   delivery_instructions = col_character(),
##   ..   trans_id = col_character()
##   .. )
```

```
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_delivery_tracking_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 4] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ tracking_number        : chr [1:1000] "581-6200" "004-1482" "064-9023" "657-4120" ...
##  $ shipment_method        : chr [1:1000] "express" "next day" "express" "standard" ...
##  $ estimated_delivery_date: Date[1:1000], format: "2023-06-23" "2023-11-21" ...
##  $ estimated_delivery_time: 'hms' num [1:1000] 11:20:33 14:41:18 07:27:46 15:10:18 ...
##   ..- attr(*, "units")= chr "secs"
##  - attr(*, "spec")=
##   .. cols(
##   ..   tracking_number = col_character(),
##   ..   shipment_method = col_character(),
##   ..   estimated_delivery_date = col_date(format = ""),
##   ..   estimated_delivery_time = col_time(format = "")
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_estimated_delivery_date_dataset.csv has above data structure"
## spc_tbl_ [1,681 x 4] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ customer_id: chr [1:1681] "YTS-92438" "BWU-36083" "CLZ-73501" "KCQ-71974" ...
##  $ order_id   : chr [1:1681] "AAD-4091" "AAK-0526" "AAK-6361" "ADJ-5614" ...
##  $ order_date : Date[1:1681], format: "2023-11-10" "2024-02-09" ...
##  $ order_time : 'hms' num [1:1681] 05:43:29 14:20:43 20:29:45 23:34:47 ...
##   ..- attr(*, "units")= chr "secs"
##  - attr(*, "spec")=
##   .. cols(
##   ..   customer_id = col_character(),
##   ..   order_id = col_character(),
##   ..   order_date = col_date(format = ""),
##   ..   order_time = col_time(format = "")
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_order_datetime_dataset.csv has above data structure"
## spc_tbl_ [3,401 x 4] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ customer_id: chr [1:3401] "YTS-92438" "YTS-92438" "BWU-36083" "BWU-36083" ...
##  $ order_id   : chr [1:3401] "AAD-4091" "AAD-4091" "AAK-0526" "AAK-0526" ...
##  $ product_id : chr [1:3401] "42-811-3974" "72-217-8555" "85-279-1314" "43-612-9451" ...
##  $ product_qty: num [1:3401] 9 10 5 19 16 20 14 4 13 10 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   customer_id = col_character(),
##   ..   order_id = col_character(),
##   ..   product_id = col_character(),
##   ..   product_qty = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_order_products_info_dataset.csv has above data structure"
## spc_tbl_ [88 x 2] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ category_name     : chr [1:88] "Beauty" "Books" "Clothing" "Electronics" ...
##  $ parent_category_id: chr [1:88] NA NA NA NA ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   category_name = col_character(),
##   ..   parent_category_id = col_character()
##   .. )
```

```
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_product_category_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 9] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ product_id    : chr [1:1000] "34-100-2931" "60-215-8627" "10-395-8862" "84-465-9981" ...
##  $ product_name  : chr [1:1000] "Unveiled: The Life of a Visionary" "Learn & Play Alphabet Blocks" "
##  $ product_weight: num [1:1000] 4322 614 1942 3825 471 ...
##  $ product_length: num [1:1000] 67 24 65 74 67 83 75 63 68 67 ...
##  $ product_height: num [1:1000] 35 22 10 73 31 87 100 47 33 92 ...
##  $ product_width : num [1:1000] 30 98 30 47 87 94 100 56 61 58 ...
##  $ product_price : num [1:1000] 11.6 30.8 26.3 43.2 14.8 ...
##  $ supplier_id   : chr [1:1000] "RSH-48812" "HNW-87364" "QIS-31117" "TJZ-16253" ...
##  $ category_name : chr [1:1000] "Biography" "Educational Toys" "Fresh Produce" "History" ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   product_id = col_character(),
##   ..   product_name = col_character(),
##   ..   product_weight = col_double(),
##   ..   product_length = col_double(),
##   ..   product_height = col_double(),
##   ..   product_width = col_double(),
##   ..   product_price = col_double(),
##   ..   supplier_id = col_character(),
##   ..   category_name = col_character()
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_product_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 4] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ promo_code         : chr [1:1000] "BU86M505PYD" "BG70Z584RFB" "JI24S173EUJ" "FU87P552XKO" ...
##  $ promo_start_date   : Date[1:1000], format: "2023-07-07" "2023-11-09" ...
##  $ promo_expire_date  : Date[1:1000], format: "2023-12-27" "2024-03-03" ...
##  $ percentage_discount: num [1:1000] 50 25 45 45 40 30 35 10 40 45 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   promo_code = col_character(),
##   ..   promo_start_date = col_date(format = ""),
##   ..   promo_expire_date = col_date(format = ""),
##   ..   percentage_discount = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_promotion_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 8] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ supplier_id      : chr [1:1000] "XTE-60952" "WLS-09227" "RCO-72629" "KCV-52154" ...
##  $ supplier_name    : chr [1:1000] "Hyatt and Sons" "Huels-Krajcik" "Morissette LLC" "Koepp, Bechtel
##  $ supplier_phone   : chr [1:1000] "+44 336 825 7695" "+44 515 420 8651" "+44 213 964 1394" "+44 404
##  $ supplier_email   : chr [1:1000] "mkilpatrick0@nyu.edu" "cbritt1@unesco.org" "ctrussler2@hao123.co
##  $ supplier_building: num [1:1000] 796 881 66 921 254 968 44 554 774 679 ...
##  $ supplier_street  : chr [1:1000] "Garden Road" "Meadow Road" "Garden Road" "River Road" ...
##  $ supplier_city    : chr [1:1000] "London" "Birmingham" "Birmingham" "London" ...
##  $ supplier_postcode: chr [1:1000] "KY2Y 6JZ" "B12 7TB" "DE9W 6WF" "W1 9SG" ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   supplier_id = col_character(),
##   ..   supplier_name = col_character(),
##   ..   supplier_phone = col_character(),
```

```
##   ..   supplier_email = col_character(),
##   ..   supplier_building = col_double(),
##   ..   supplier_street = col_character(),
##   ..   supplier_city = col_character(),
##   ..   supplier_postcode = col_character()
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_supplier_dataset.csv has above data structure"
## spc_tbl_ [1,000 x 4] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ trans_id  : chr [1:1000] "EHD-784624" "SIZ-926836" "GEP-276863" "YRS-371629" ...
##  $ order_id  : chr [1:1000] "AAD-4091" "AAK-0526" "ADJ-6838" "ADV-4775" ...
##  $ trans_date: Date[1:1000], format: "2023-11-10" "2024-02-09" ...
##  $ trans_time: 'hms' num [1:1000] 07:56:40 15:23:52 12:30:16 14:57:31 ...
##   ..- attr(*, "units")= chr "secs"
##  - attr(*, "spec")=
##   .. cols(
##   ..   trans_id = col_character(),
##   ..   order_id = col_character(),
##   ..   trans_date = col_date(format = ""),
##   ..   trans_time = col_time(format = "")
##   .. )
##  - attr(*, "problems")=<externalptr>
## [1] "The file: hi_transaction_dataset.csv has above data structure"
```

3. Check for NULL values

```r
all_files <- list.files("Dataset/")

for (variable in all_files) {
    this_filepath <- paste0("Dataset/", variable)
    this_file_contents <- readr::read_csv(this_filepath)
    null <- sum(is.na(this_file_contents))

    print(paste0("The file: ", variable, " has a total of ",
        null, " NULL values"))
}
```

```
## [1] "The file: hi_actual_delivery_date_dataset.csv has a total of 172 NULL values"
## [1] "The file: hi_customer_basic_info_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_customer_membership_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_delivery_tracking_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_estimated_delivery_date_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_order_datetime_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_order_products_info_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_product_category_dataset.csv has a total of 8 NULL values"
## [1] "The file: hi_product_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_promotion_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_supplier_dataset.csv has a total of 0 NULL values"
## [1] "The file: hi_transaction_dataset.csv has a total of 0 NULL values"
```

4. Check that each primary key is unique in each table except for order

```r
all_files <- list.files("Dataset/")

```

```r
for (variable in all_files) {
    this_filepath <- paste0("Dataset/", variable)
    this_file_contents <- readr::read_csv(this_filepath)
    hi <- nrow(unique(this_file_contents[, 1])) == nrow(this_file_contents)

    print(paste0("The file: ", variable, " has unique primary key ",
        hi, " columns"))
}
```

```
## [1] "The file: hi_actual_delivery_date_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_customer_basic_info_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_customer_membership_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_delivery_tracking_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_estimated_delivery_date_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_order_datetime_dataset.csv has unique primary key FALSE columns"
## [1] "The file: hi_order_products_info_dataset.csv has unique primary key FALSE columns"
## [1] "The file: hi_product_category_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_product_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_promotion_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_supplier_dataset.csv has unique primary key TRUE columns"
## [1] "The file: hi_transaction_dataset.csv has unique primary key TRUE columns"
```

For order dataset

We have a composite primary key orderdate_dataset composed of 2 attribute and a composite primary key orderproductsinfo_dataset composed of 3 attribute, we'll check these one separately.

```r
orderdate_dataset <- read.csv("Dataset/hi_order_datetime_dataset.csv")
orderproductsinfo_dataset <- read.csv("Dataset/hi_order_products_info_dataset.csv")
nrow(unique(orderdate_dataset[, 1:2])) == nrow(orderdate_dataset)
```

```
## [1] TRUE
```

```r
nrow(unique(orderproductsinfo_dataset[, 1:3])) == nrow(orderproductsinfo_dataset)
```

```
## [1] TRUE
```

```r
# sum(nrow(unique(orders[,1:2])))
# length((unique(orders$cutomer_id)))
# length((unique(orders$order_id))) The file:
# hi_order_dataset.csv has unique primary composite key
# TRUE columns
```

In Customer dataset, there are e-mail and phone number columns, which required specific format checks. For e-mail, special characters "@" and ending domain must be validated. For phone number, IT must be ensured to have 10 numeric characters.

5. Validate phone number

```r
# Supplier
supplier_dataset <- read.csv("Dataset/hi_supplier_dataset.csv")
length(grepl("\\+44\\s\\d{3}\\s\\d{3}\\s\\d{4}", supplier_dataset$supplier_phone)) ==
    nrow(supplier_dataset)
```

```
## [1] TRUE
```

```r
# Customer
customer_basic_info_dataset <- read.csv("Dataset/hi_customer_basic_info_dataset.csv")
length(grepl("\\+44\\s\\d{3}\\s\\d{3}\\s\\d{4}", customer_basic_info_dataset$customer_phone)) ==
    nrow(customer_basic_info_dataset)
```

```
## [1] TRUE
```

6. Validate email address

```r
# Supplier
length(grepl("@", supplier_dataset$supplier_email)) == nrow(supplier_dataset)
```

```
## [1] TRUE
```

```r
# Consumer
length(grepl("@", customer_basic_info_dataset$customer_email)) ==
    nrow(customer_basic_info_dataset)
```

```
## [1] TRUE
```

Import Datasets

Then we imported csv files into SQL table for all datasets, including the ones we generated after normalization.

For loop to read csv and then import into sql

```r
# Read datasets order
order_datetime_dataset <- read.csv("Dataset/hi_order_datetime_dataset.csv")
order_products_info_dataset <- read.csv("Dataset/hi_order_products_info_dataset.csv")

# delivery

actual_delivery_date_dataset <- read.csv("Dataset/hi_actual_delivery_date_dataset.csv")
delivery_tracking_dataset <- read.csv("Dataset/hi_delivery_tracking_dataset.csv")
estimated_delivery_date_dataset <- read.csv("Dataset/hi_estimated_delivery_date_dataset.csv")

# customer
customer_basic_info_dataset <- read.csv("Dataset/hi_customer_basic_info_dataset.csv")
customer_membership_dataset <- read.csv("Dataset/hi_customer_membership_dataset.csv")
product_dataset <- read.csv("Dataset/hi_product_dataset.csv")
product_category_dataset <- read.csv("Dataset/hi_product_category_dataset.csv")
promotion_dataset <- read.csv("Dataset/hi_promotion_dataset.csv")
supplier_dataset <- read.csv("Dataset/hi_supplier_dataset.csv")
transaction_dataset <- read.csv("Dataset/hi_transaction_dataset.csv")
```

```r
dbWriteTable(connection, "product", product_dataset, append = TRUE,
    row.names = FALSE)
dbWriteTable(connection, "product_category", product_category_dataset,
    append = TRUE, row.names = FALSE)
dbWriteTable(connection, "promotion", promotion_dataset, append = TRUE,
    row.names = FALSE)
dbWriteTable(connection, "supplier", supplier_dataset, append = TRUE,
    row.names = FALSE)
dbWriteTable(connection, "transaction", transaction_dataset,
```

```
    append = TRUE, row.names = FALSE)

# order
dbWriteTable(connection, "order_datetime", order_datetime_dataset,
    append = TRUE, row.names = FALSE)
dbWriteTable(connection, "order_products_info", order_products_info_dataset,
    append = TRUE, row.names = FALSE)

# delivery
dbWriteTable(connection, "actual_delivery_date", actual_delivery_date_dataset,
    append = TRUE, row.names = FALSE)
dbWriteTable(connection, "delivery_tracking", delivery_tracking_dataset,
    append = TRUE, row.names = FALSE)
dbWriteTable(connection, "estimated_delivery_date", estimated_delivery_date_dataset,
    append = TRUE, row.names = FALSE)

# customer
dbWriteTable(connection, "customer_membership", customer_membership_dataset,
    append = TRUE, row.names = FALSE)
dbWriteTable(connection, "customer_basic_info", customer_basic_info_dataset,
    append = TRUE, row.names = FALSE)
```

Check the tables using select

```sql
SELECT * FROM "product" LIMIT 5
```

Table 16: 5 records

product_id	supplier_id	category_name	product_name	product_weight	product_length	product_height	product_width	product_price
34-100-2931	RSH-48812	Biography	Unveiled: The Life of a Visionary	4322	67	35	30	11.62
60-215-8627	HNW-87364	Educational Toys	Learn & Play Alphabet Blocks	614	24	22	98	30.83
10-395-8862	QIS-31117	Fresh Produce	Organic Harvest Bundle	1942	65	10	30	26.30
84-465-9981	TJZ-16253	History	Epochs in Time: A Historical Analysis	3825	74	73	47	43.25
51-355-5771	OTM-80847	Mystery	Whispers in the Shadows: Mystery Novel	471	67	31	87	14.78

```sql
SELECT * FROM "product_category" LIMIT 5
```

Table 17: 5 records

category_name	parent_category_id
Beauty	
Books	

category_name	parent_category_id
Clothing	
Electronics	
Grocery	

```sql
SELECT * FROM "promotion" LIMIT 5
```

Table 18: 5 records

promo_code	promo_start_date	promo_expire_date	percentage_discount
BU86M505PYD	2023-07-07	2023-12-27	50
BG70Z584RFB	2023-11-09	2024-03-03	25
JI24S173EUJ	2024-03-20	2024-07-07	45
FU87P552XKO	2023-11-24	2024-04-06	45
SD70E981QNT	2024-02-16	2024-08-04	40

```sql
SELECT * FROM "supplier" LIMIT 5
```

Table 19: 5 records

supplier_id	supplier_name	supplier_phone	supplier_email	supplier_building	supplier_street	supplier_city	supplier_postcode
XTE-60952	Hyatt and Sons	+44 336 825 7695	mkilpatrick0@nyu.edu	796	Garden Road	London	KY2Y 6JZ
WLS-09227	Huels-Krajcik	+44 515 420 8651	cbritt1@unesco.org	881	Meadow Road	Birmingham	B12 7TB
RCO-72629	Morissette LLC	+44 213 964 1394	ctrussler2@hao123.com	66	Garden Road	Birmingham	DE9W 6WF
KCV-52154	Koepp, Bechtelar and Weimann	+44 404 383 6574	egoddman3@mtv.com	921	River Road	London	W1 9SG
UTZ-90791	Stamm-Schmidt	+44 312 442 5804	lharome4@oaic.gov.au	254	Lake Road	Bristol	L43 3FX

```sql
SELECT * FROM "transaction" LIMIT 5
```

Table 20: 5 records

trans_id	order_id	trans_date	trans_time
EHD-784624	AAD-4091	2023-11-10	07:56:40
SIZ-926836	AAK-0526	2024-02-09	15:23:52
GEP-276863	ADJ-6838	2023-08-02	12:30:16
YRS-371629	ADV-4775	2023-10-26	14:57:31
VMS-478374	ADX-1928	2024-02-28	00:15:39

Order:

```sql
SELECT * FROM "order_datetime" LIMIT 5
```

Table 21: 5 records

order_id	customer_id	order_date	order_time
AAD-4091	YTS-92438	2023-11-10	05:43:29
AAK-0526	BWU-36083	2024-02-09	14:20:43
AAK-6361	CLZ-73501	2024-03-28	20:29:45
ADJ-5614	KCQ-71974	2023-11-19	23:34:47
ADJ-6838	GSB-19226	2023-08-02	11:28:04

```
SELECT * FROM "order_products_info" LIMIT 5
```

Table 22: 5 records

order_id	customer_id	product_id	product_qty
AAD-4091	YTS-92438	42-811-3974	9
AAD-4091	YTS-92438	72-217-8555	10
AAK-0526	BWU-36083	85-279-1314	5
AAK-0526	BWU-36083	43-612-9451	19
AAK-0526	BWU-36083	42-665-9904	16

Delivery

```
SELECT * FROM "actual_delivery_date" LIMIT 5
```

Table 23: 5 records

tracking_number	tracking_status	actual_delivery_date	actual_delivery_time
581-6200	Delivered	2023-06-24	12:45:44
004-1482	Delivered	2023-11-22	08:18:48
064-9023	In process	NA	NA
657-4120	Delivered	2024-02-01	07:43:05
983-4613	Delivered	2023-08-12	11:01:41

```
SELECT * FROM "delivery_tracking" LIMIT 5
```

Table 24: 5 records

tracking_number	trans_id	delivery_instructions
581-6200	AAA-067232	ring bell
004-1482	AAC-152328	delivery box
064-9023	AAD-850184	ring bell
657-4120	AAR-680860	leave infront of door
983-4613	AAT-296188	ring bell

```
SELECT * FROM "estimated_delivery_date" LIMIT 5
```

Table 25: 5 records

tracking_number	shipment_method	estimated_delivery_date	estimated_delivery_time
581-6200	express	2023-06-23	11:20:33
004-1482	next day	2023-11-21	14:41:18
064-9023	express	2024-03-06	07:27:46
657-4120	standard	2024-02-01	15:10:18
983-4613	next day	2023-08-11	16:02:04

Customer:

```sql
SELECT * FROM "customer_membership" LIMIT 5
```

Table 26: 5 records

customer_id	customer_membership	delivery_fee
NAT-21446	membership	0.00
MQV-12400	not membership	4.99
MLY-44705	not membership	5.99
RFE-59474	membership	0.00
WBO-40739	membership	0.00

```sql
SELECT * FROM "customer_basic_info" LIMIT 5
```

Table 27: 5 records

customer_id	promo_code	customer_firstname	customer_lastname	customer_title	customer_phone	customer_email	customer_building	customer_street	customer_city	customer_postcode
NAT-21446	VS04A935QNO	Mike	Berriball	Dr	+44 482 422 6609	mberriball0@abc.net.au	103	Willow Street	Birmingham	B1D 6RT
MQV-12400	OQ50R1A0HWT	Antoinet	Lujan	Mr	+44 941 356 9889	alujan1@qq.com	436	Spruce Street	Birmingham	G1A 8DD
MLY-44705	DU63L727XKV	Moria	Llewellen	Honorable	+44 398 412 8484	mllewellen2@hud.gov	861	Willow Street	Bristol	G4H 0NH
RFE-59474	IW96D852N6T	Ichabod	Philson	Honorable	+44 114 708 3717	iphilson3@github.com	271	Maple Street	Bristol	M04 5UF
WBO-40739	IX31K072LEZ	Leena	Strangeway	Mrs	+44 782 865 8414	lstrangeway4@utexas.edu	107	Ash Street	Birmingham	M8 3LL

Calculated Field we created as we mentioned above for Normalization

Transaction amount

```sql
SELECT o.order_id, prm.percentage_discount, m.delivery_fee, SUM(p.product_price*o.product_qty) AS order_
FROM "order_products_info" o, "product" p, "promotion" prm, "customer_basic_info" c, "customer_membershi
```

```
WHERE o.customer_id = m.customer_id AND o.product_id = p.product_id AND c.promo_code = prm.promo_code AI
GROUP BY
    o.order_id;
```

Table 28: Displaying records 1 - 10

order_id	percentage_discount	delivery_fee	order_price	trans_amount
AAD-4091	25	0.00	822.15	616.61
AAK-0526	30	0.00	767.93	537.55
AAK-6361	25	6.99	1058.78	801.08
ADJ-5614	45	3.99	193.16	110.23
ADJ-6838	35	2.99	681.37	445.88
ADV-4775	45	5.99	1113.84	618.60
ADV-7947	20	5.99	116.87	99.49
ADX-1928	45	0.00	892.56	490.91
ADX-2356	40	0.00	350.07	210.04
AFD-0715	15	0.00	827.32	703.22

Store natively it in R

```
# Customer
customer_membership <- dbReadTable(connection, "customer_membership")
customer_basic_info <- dbReadTable(connection, "customer_basic_info")

# Delivery
actual_delivery_date <- dbReadTable(connection, "actual_delivery_date")
delivery_tracking <- dbReadTable(connection, "delivery_tracking")
estimated_delivery_date <- dbReadTable(connection, "estimated_delivery_date")

# Order
order_datetime <- dbReadTable(connection, "order_datetime")
order_products_info <- dbReadTable(connection, "order_products_info")

product <- dbReadTable(connection, "product")
product_category <- dbReadTable(connection, "product_category")
promotion <- dbReadTable(connection, "promotion")
supplier <- dbReadTable(connection, "supplier")
transaction <- dbReadTable(connection, "transaction")
```

List tables

```
RSQLite::dbListTables(connection)
```

```
##  [1] "actual_delivery_date"            "combined_delivery_dataset"
##  [3] "customer"                        "customer_basic_info"
##  [5] "customer_membership"             "customer_memebership"
##  [7] "delivered_deliveries_dataset"    "delivery"
##  [9] "delivery_tracking"               "estimated_delivery_date"
## [11] "order"                           "order_datetime"
## [13] "order_products_datetime_dataset" "order_products_info"
## [15] "product"                         "product_category"
```

```
## [17] "product_procat_join_dataset"     "promotion"
## [19] "supplier"                        "transaction"
```

Disconnect SQL

```
# RSQLite::dbDisconnect(connection)
```

Part 3: Data Pipeline Generation

Part 3.1: GitHub Repository and Workflow Setup

The purpose was to automate the process of updating and maintaining an R project on GitHub, making it easier for our team to collaborate and keep our project up to date.

The name of the code is "Update Repo with result"

Our primary objective was to utilize GitHub repositories for efficient version control of our project. Initially, we transformed our R Markdown file into an R script, encompassing all the steps outlined in from parts 1.2 - 2.2. We proceeded to load the requisite files into a SQLite database, creating tables and importing datasets from the "Dataset" file. Despite solely utilizing the R script, we ensured all pertinent files were maintained within the repository. This was achieved by leveraging the repository's URL and executing commits and pushes whenever modifications were made. Subsequently, we established a new repository on GitHub and extended invitations to collaborators, granting them appropriate access levels.

Part 3.2: GitHub Actions for Continuous Integration

For the implementation of GitHub Actions for Continuous Integration, we aimed to streamline our project's development workflow. This involved adopting continuous integration practices to automate tasks such as data validation, database updates, and data analysis. For instance, whenever changes occurred in the repository, such as importing new data, the updates were seamlessly integrated into the database, and relevant outputs were generated only if significant changes were detected. Scheduled workflows were set to run at regular intervals, such as every three hours, ensuring consistent and efficient execution of these tasks.

Within workflow, we configured the R environment and cached any necessary R packages that were not already installed. Essential packages such as "ggplot" and "dplyr" were installed for data visualization purposes. The workflow then executed the R script, incorporating any changes made during the process. Finally, all modifications were committed to the local repository and subsequently pushed to the main branch using a unique access token for authentication. This comprehensive approach to CI enabled seamless integration of updates and ensured the project's integrity and efficiency.

The code is added below:

```
name: Update Repo with result

on:
#  schedule:
#    - cron: '0 */3 * * *' # Run every 3 hours
  push:
    branches: [ master ]
    paths:
    - '.github/workflows/**'
    - 'R_codelast'
    - 'Dataset/**'

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@v2
      with:
        path: ${{ env.R_LIBS_USER }}
        key: ${{ runner.os }}-r-${{ hashFiles('**/lockfile') }}
        restore-keys: |
          ${{ runner.os }}-r-
    - name: Install packages
      if: steps.cache.outputs.cache-hit != 'true'
      run: |
        Rscript -e 'install.packages(c("ggplot2", "dplyr", "readr", "RSQLite"))'

    - name: Execute R script
      run: |
        Rscript R_codelast.R
    - name: Add files
      run: |
       git config --global --unset-all "http.https://github.com/.extraheader" || true
       git config --global user.email "savvinanicolaou@gmail.com"
       git config --global user.name "savvinanic"
       git add .
    - name: Commit files
      run: |
        git commit -m "Update Database"
    - name: Push changes
      uses: ad-m/github-push-action@v0.6.0
      with:
        github_token: ${{ secrets.MY_TOKEN }}
        branch: master
```

Part 4: Data Analysis and Reporting

Data Visualisation

In this section we created diverse graphs including histograms, line and pie charts and tables in SQL. This is vital as it will provide us with insights about potential issues, customer satisfaction and experience, if they are any areas of improvement in various operations like delivery service, sales by city, membership and promotions. Below are listed all titles and different visualizations we generated.

1. Product Category vs Count
2. Sales by Category
3. Product Category vs Average Order quantity per order
4. Product Category vs Average Order quantity per month
5. Number of orders placed each hour of the day
6. Compute the average Delivery delay by the three types of shipment methods

7. Percentage of customers having a Membership
8. Sales by Membership Status
9. Order delay - Membership
10. Monthly Revenue by City
11. Top 5 Products by Sales Volume and Total Sales Profit After Discount
12. Top 5 products sold and percentage discount applied
13. Top 10 customers with the highest transaction amount, percentage discount applied and products bought
14. Supplier sales volume
15. Supplier revenue
16. Sales by Category

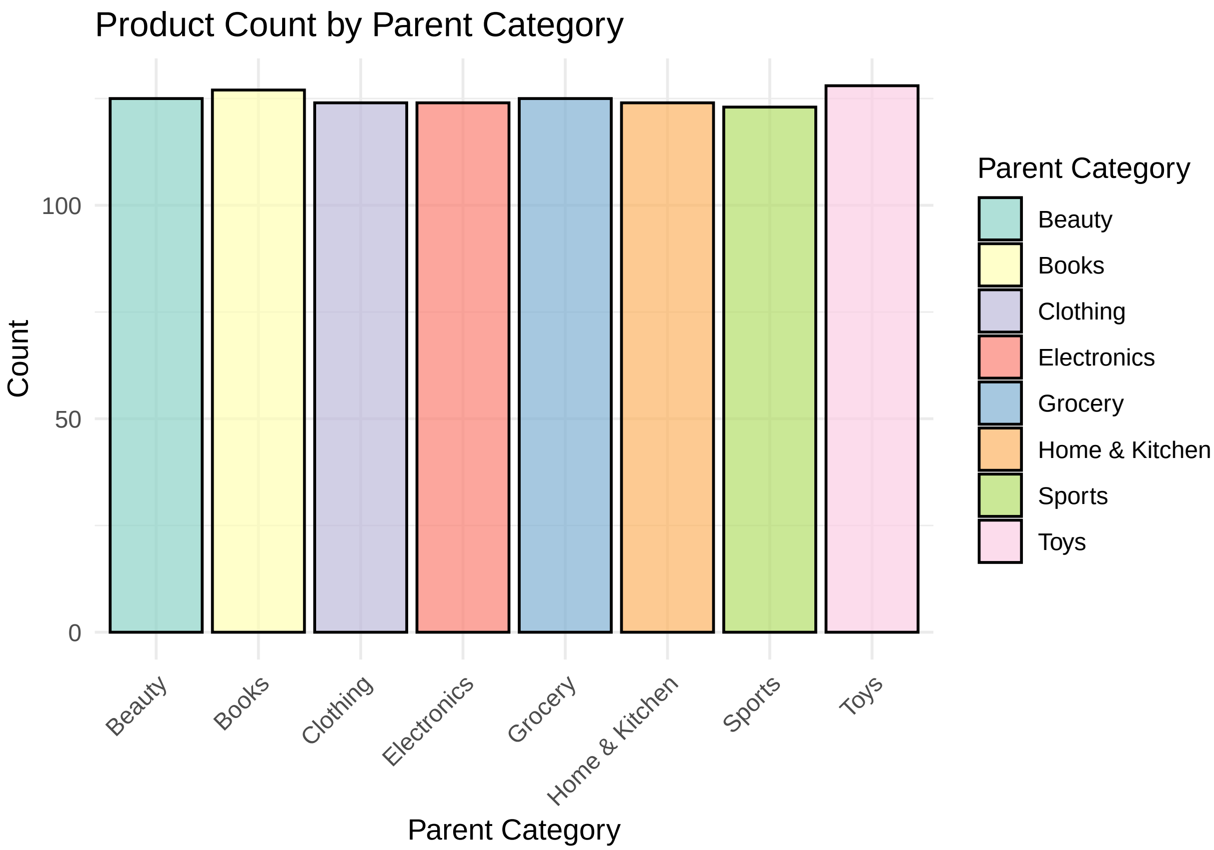
```
## -- Attaching core tidyverse packages ----------------------- tidyverse 2.0.0 --
## v forcats   1.0.0     v stringr   1.5.1
## v lubridate 1.9.3     v tibble    3.2.1
## v purrr     1.0.2     v tidyr     1.3.1
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
##
## Attaching package: 'gridExtra'
##
##
## The following object is masked from 'package:dplyr':
##
##     combine
```

1. Product Category vs Count

The graph provides a clear overview of the diversity and distribution of products within different categories, informing strategic decisions regarding resource allocation, market segmentation, and competitive positioning.

```r
product_procat_join <- dbGetQuery(connection, "
  SELECT p.*, pc.parent_category_id
  FROM product AS p
  INNER JOIN product_category AS pc ON p.category_name = pc.category_name
")
```

```r
product_procat_join %>%
  group_by(parent_category_id) %>%
  summarise(count = n()) %>%
  ggplot(aes(x = factor(parent_category_id), y = count, fill = factor(parent_category_id))) +
  geom_bar(stat = "identity", position = "dodge", color = "black", alpha = 0.7) +
  labs(title = "Product Count by Parent Category",
       x = "Parent Category",
       y = "Count") +
  scale_fill_brewer(name = "Parent Category", palette = "Set3") +
  theme_minimal() +  # Apply minimal theme
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



- There's an equal distribution of type of products stored in our E-Commerce store.

```
dbWriteTable(connection, "product_procat_join_dataset", product_procat_join,
    overwrite = TRUE)
```

2. Sales by Category

This graph highlights which categories provide the highest number of total sales. This also illustrates where our E-commerce strengthens in terms of product category, which will help us determine which category to focus on to increase our revenue.

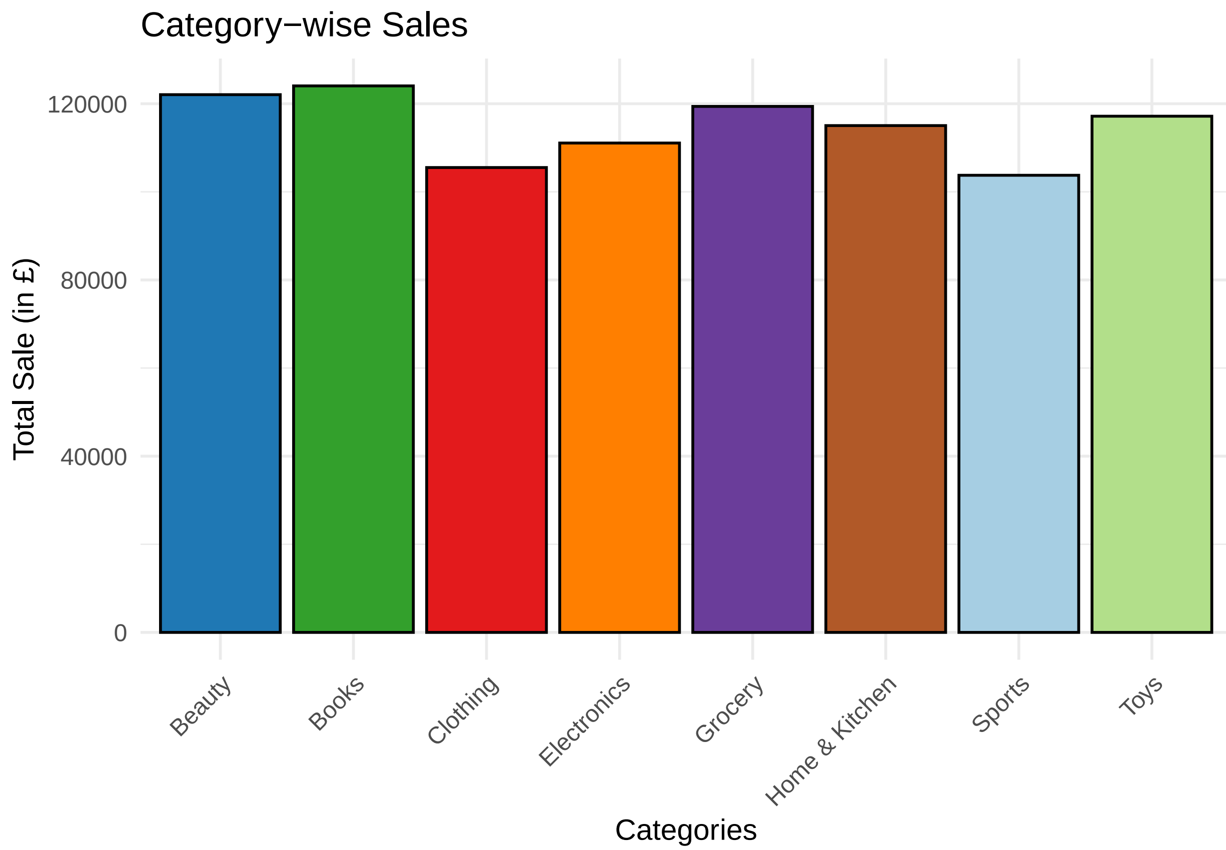
```
order_product_join <- dbGetQuery(connection, "
SELECT op.order_id, op.customer_id, op.product_id, p.parent_category_id, op.product_qty, p.product_pric
FROM `order_products_info` AS op
INNER JOIN order_datetime AS od ON op.order_id = od.order_id
INNER JOIN product_procat_join_dataset AS p ON op.product_id = p.product_id
")
```

```
my_colors <- c("#1f78b4", "#33a02c", "#e31a1c", "#ff7f00", "#6a3d9a", "#b15928", "#a6cee3", "#b2df8a",

category_wise_sales <- order_product_join %>%
  group_by(parent_category_id) %>%
  summarise(Total_sales = sum(product_qty*product_price))

ggplot(category_wise_sales, aes(x = factor(parent_category_id), y = Total_sales, fill = factor(parent_c
  geom_bar(stat = "identity", color = "black") +
  scale_fill_manual(values = my_colors) +
```

```r
  labs(x = "Categories", y = "Total Sale (in £)", title = "Category-wise Sales") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),  # Rotate x-axis labels
        legend.position = "none")
```



- Beauty, books and grocery are the top three categories with the highest number of total sales. However, all categories have very similar total number of sales. Therefore, we might need to focus on the ones that lie within our company's marketing objectives.

3. Product Category vs Average Order quantity per order

The graph provides insights for inventory management by ensuring sufficient stock of popular items while minimizing excess inventory for less frequently ordered products. Additionally, it enables targeted promotions for products with higher average quantities and facilitates personalized product recommendations for customers.

```r
orderqty_category_join <- dbGetQuery(connection, "
SELECT pc.parent_category_id, AVG(o.product_qty) AS avg_order_quantity
FROM `order_products_info` AS o
INNER JOIN product AS p ON o.product_id = p.product_id
INNER JOIN product_category AS pc ON p.category_name = pc.category_name
GROUP BY pc.parent_category_id
")
```

```r
ggplot(orderqty_category_join, aes(x = factor(parent_category_id),
    y = avg_order_quantity, fill = parent_category_id)) + geom_bar(stat = "identity",
    position = "dodge", color = "black", alpha = 0.7) + labs(title = "Avg. Order Quantity by Product Ca
    x = "Product Category", y = "Avg. Order Quantity / Order") +
```

```
    scale_fill_discrete(name = "Product Category") + theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

- We observe that two products of the same category are usually bought together per order.

4. Product Category vs Average Order quantity per month

These plots visualize average order quantity trends on a monthly basis that allows us to identify seasonal patterns and fluctuations in customer purchasing behavior over time. We also examine trends within specific categories to gain a deeper understanding of which product categories drive the most sales and how their performance varies over time.

```
order_products_datetime <- dbGetQuery(connection, "
SELECT o.*, op.product_id, op.product_qty
FROM `order_datetime` AS o
INNER JOIN order_products_info AS op ON o.order_id = op.order_id
")
```

```
dbWriteTable(connection, "order_products_datetime_dataset", order_products_datetime,
    overwrite = TRUE)
```

```
monthly_orderqty_category_join <- dbGetQuery(connection, "
SELECT pc.parent_category_id, o.order_date, o.product_qty
FROM `order_products_datetime_dataset` AS o
INNER JOIN product AS p ON o.product_id = p.product_id
INNER JOIN product_category AS pc ON p.category_name = pc.category_name
")
```

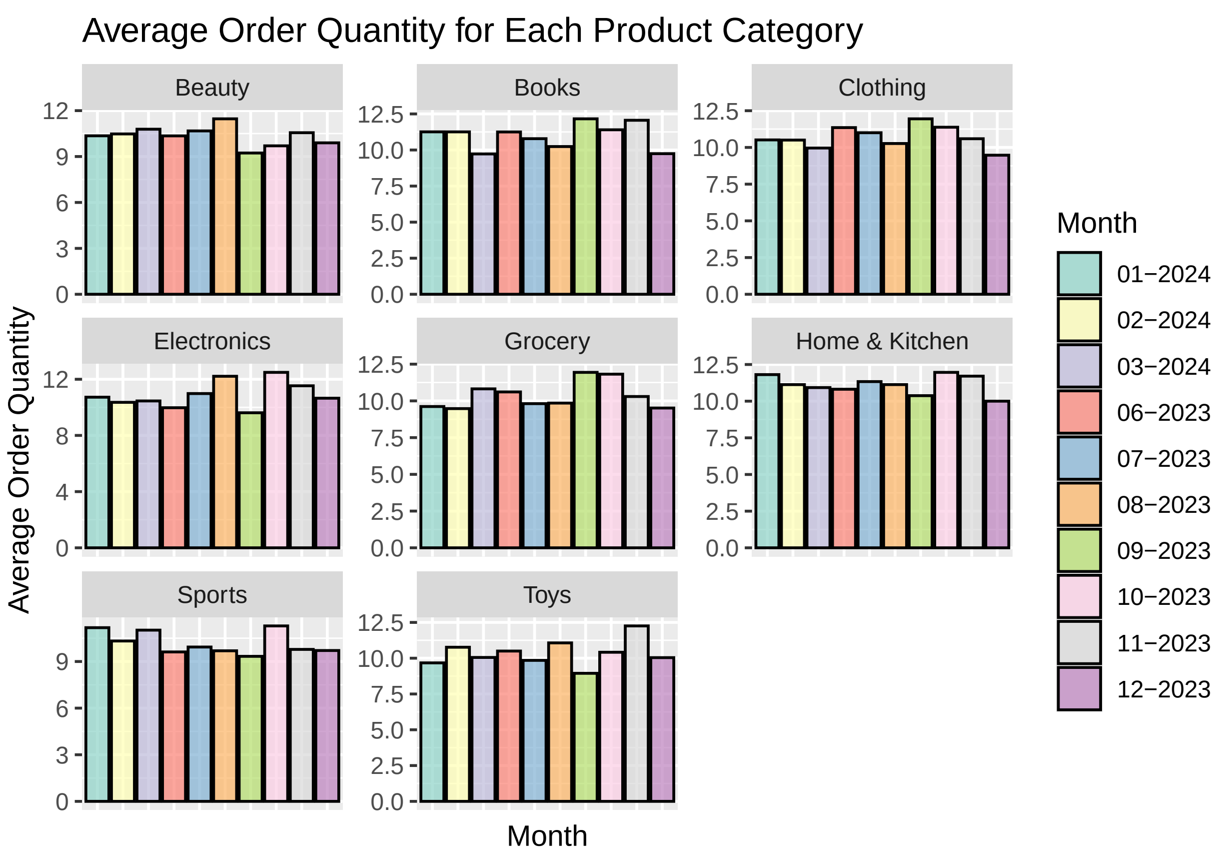
```r
# Convert order_date to date format
monthly_orderqty_category_join <- monthly_orderqty_category_join %>%
  mutate(order_date = as.Date(order_date))

# Extract month from order_date
monthly_orderqty_category_join <- monthly_orderqty_category_join %>%
  mutate(month = format(order_date, "%m-%Y"))

# Calculate average order quantity for each product and each month
avg_order_quantity <- monthly_orderqty_category_join %>%
  group_by(parent_category_id, month) %>%
  summarise(avg_qty = mean(product_qty))
```

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

```r
# Per product category
ggplot(avg_order_quantity, aes(x = month, y = avg_qty, fill = month)) +
  geom_bar(stat = "identity", position = "dodge", color = "black", alpha = 0.7) +
  labs(title = "Average Order Quantity for Each Product Category",
       x = "Month",
       y = "Average Order Quantity",
       fill = "Month") +
  scale_fill_brewer(palette = "Set3", name = "Month") +
  facet_wrap(~parent_category_id, scales = "free_y") +
  theme(axis.text.x = element_blank(),  # Remove x-axis labels
        axis.ticks.x = element_blank()) # Remove x-axis ticks
```



5. Number of orders placed each hour of the day

This graph allows us to optimize our operations to meet customer demand more effectively, improve efficiency, and enhance the overall shopping experience. Moreover, we can schedule marketing communications and promotions to coincide with peak ordering hours, maximizing their impact and driving sales during periods of high customer activity.

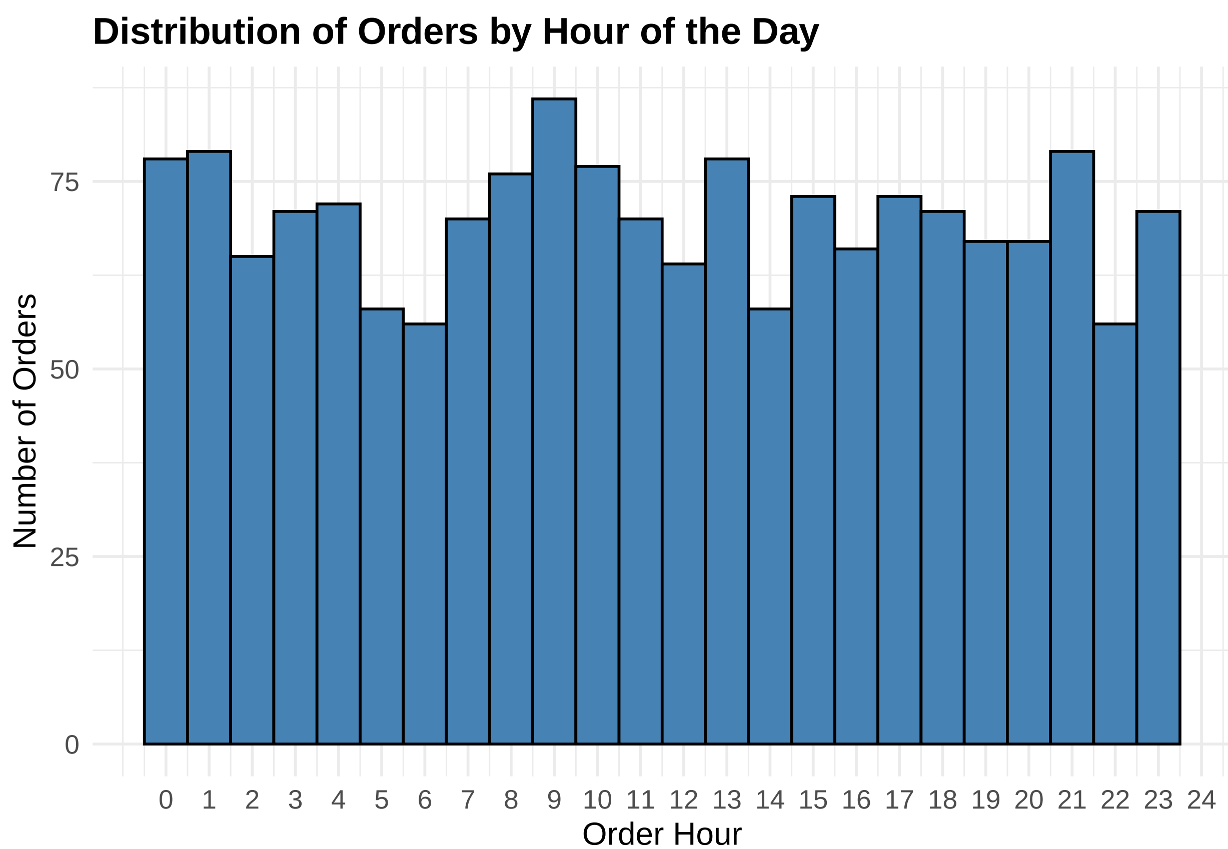
```
order_copyforanalyses <- order_datetime

# Convert 'order_time' column to POSIXct format
order_copyforanalyses$order_time <- as.POSIXct(order_copyforanalyses$order_time, format = "%H:%M:%S")

# Extract hour from 'order_time' and create a new column 'order_hour'
order_copyforanalyses$order_hour <- format(order_copyforanalyses$order_time, format = "%H")

order_copyforanalyses$order_hour <- as.numeric(order_copyforanalyses$order_hour)

# Create histogram
ggplot(order_copyforanalyses, aes(x = order_hour)) +
  geom_histogram(binwidth = 1, fill = "#4682B4", color = "black") +  # Adjusted fill color
  scale_x_continuous(breaks = seq(0, 24, by = 1)) +
  labs(x = "Order Hour", y = "Number of Orders",
       title = "Distribution of Orders by Hour of the Day") +
  theme_minimal() +
  theme(plot.title = element_text(size = 14, face = "bold"),
        axis.title = element_text(size = 12),
        axis.text = element_text(size = 10))
```



The number of orders placed in each hour remains relatively consistent, with peak times observed around 00:00 - 1:00, 9:00 - 10:00, 12:00 - 13:00, and 21:00 - 22:00.

6. Compute the average Delivery delay by the three types of shipmenet methods

This table provides a performance evaluation of our delivery service related to shipment methods. For example, if certain shipment methods consistently exhibit longer delays, we need to investigate the cause and improve delivery service. Customers expectations should be met as businesses offering faster and more reliable delivery options tend to attract and retain more customers, thereby gaining an edge in the market.

```
combined_delivery <- dbGetQuery(connection, "
SELECT e.*, a.tracking_status, a.actual_delivery_date, a.actual_delivery_time
FROM `estimated_delivery_date` AS e
INNER JOIN actual_delivery_date AS a ON a.tracking_number = e.tracking_number
")
```

```
dbWriteTable(connection, "combined_delivery_dataset", combined_delivery,
    overwrite = TRUE)
```

```
# Filter delivery data for 'Delivered' orders only
delivered_deliveries <- combined_delivery %>%
    filter(tracking_status == "Delivered")

# Convert date and time columns to POSIXct format
delivered_deliveries$estimated_delivery_datetime <- with(delivered_deliveries,
    ymd_hms(paste(delivered_deliveries$estimated_delivery_date,
        delivered_deliveries$estimated_delivery_time)))
delivered_deliveries$actual_delivery_datetime <- with(delivered_deliveries,
    ymd_hms(paste(delivered_deliveries$actual_delivery_date,
        delivered_deliveries$actual_delivery_time)))

# Calculate delay
delivered_deliveries$delay <- as.numeric(difftime(delivered_deliveries$actual_delivery_datetime,
    delivered_deliveries$estimated_delivery_datetime, units = "hours"))

# Calculate average delay
average_delay <- round(mean(delivered_deliveries$delay, na.rm = TRUE),
    2)


# Print average delay
print(average_delay)
```

```
## [1] 7.67
```

```
dbWriteTable(connection, "delivered_deliveries_dataset", delivered_deliveries,
    overwrite = TRUE)
```

```
delivered_deliveries_by_shipmentmethod <- delivered_deliveries %>%
    group_by(shipment_method) %>%
    summarise(average.delay = round(mean(delay), 2))

kable(delivered_deliveries_by_shipmentmethod, caption = "Average Delivery Delay by Shipment Method",
    col.names = c("Shipment Method", "Average Delay (hours)"))
```

Table 29: Average Delivery Delay by Shipment Method

Shipment Method	Average Delay (hours)
express	-0.38
next day	12.22
standard	11.65

- The average delay in next-day delivery is approximately 12 hours, falling short of meeting customer expectations. This discrepancy signals a need for improvement to ensure timely delivery and enhance customer satisfaction.

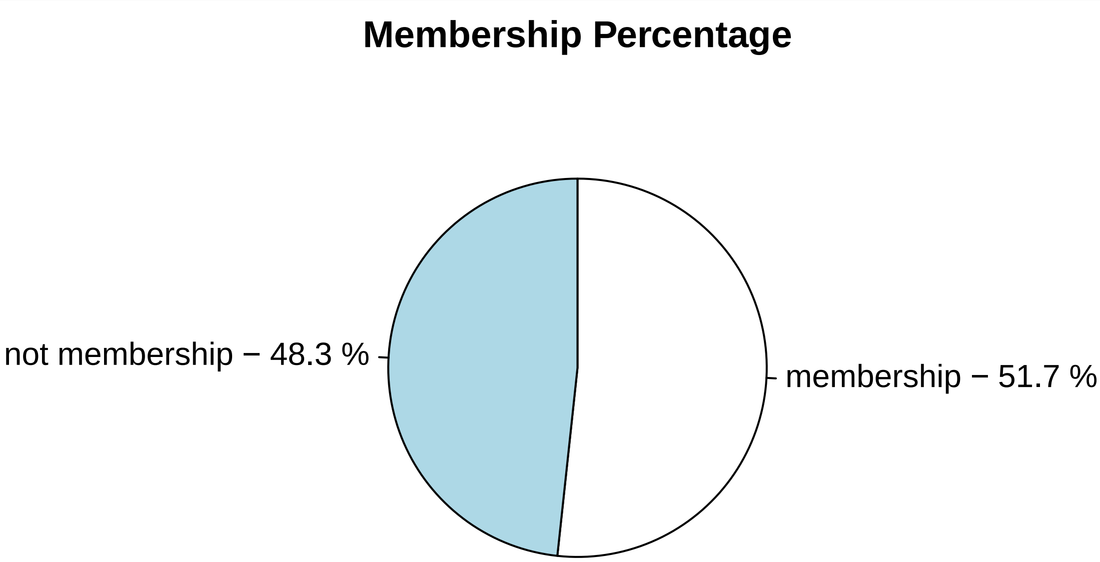
7. Percentage of customers having a Membership

The graph offers valuable insights into customer engagement and interest in our membership offerings. It underscores the potential need to incentive customers to join by providing exclusive benefits as it contributes to additional revenue streams through membership fees and subscriptions.

```
membership <- customer_membership %>%
    group_by(customer_membership) %>%
    summarise(count = n()) %>%
    mutate(total = sum(count)) %>%
    mutate(membership_percentage = (count/total) * 100)

labels <- paste(membership$customer_membership, "-", round(membership$membership_percentage,
    2), "%")

pie(membership$membership_percentage, labels = labels, main = "Membership Percentage",
    clockwise = TRUE)
```



8. Sales by Membership Status

It evaluates the effectiveness of our membership by showing total sales and if membership encourages customers to make more frequent purchases, thereby enhancing customer engagement and loyalty.

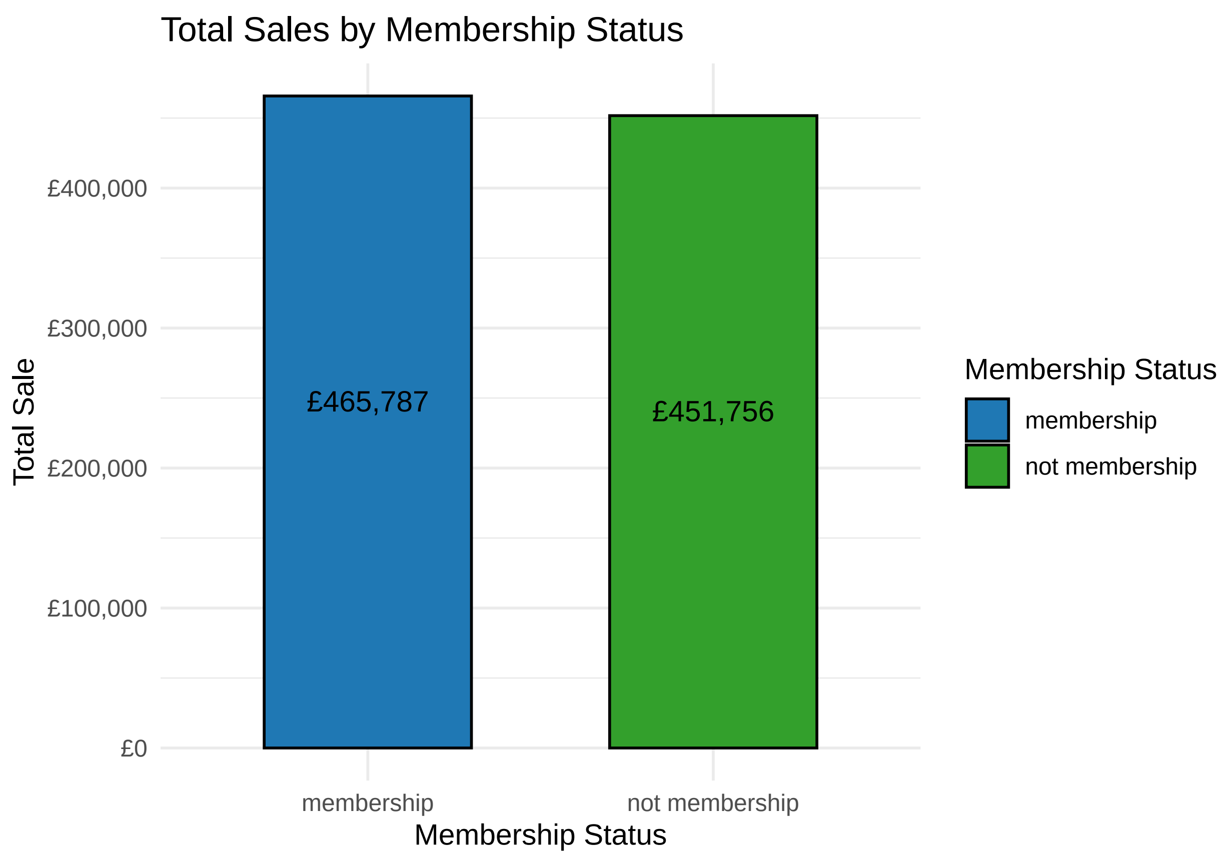
```
customer_order_join <- dbGetQuery(connection, "
SELECT c.customer_id, c.customer_membership, o.order_id, o.product_id, o.product_qty, p.product_price
FROM `customer_membership` AS c
INNER JOIN order_products_info AS o ON c.customer_id = o.customer_id
INNER JOIN product AS p ON o.product_id = p.product_id
")
```

```
customer_order_join$total_product_price <- customer_order_join$product_qty *
    customer_order_join$product_price

customer_order_join.bycustomer <- customer_order_join %>%
    group_by(customer_id) %>%
    summarise(membership_status = first(customer_membership),
        Total_sale = sum(total_product_price))
```

```
mean_totals <- customer_order_join.bycustomer %>%
    group_by(membership_status) %>%
    summarise(Total_sale = sum(Total_sale))

ggplot(mean_totals, aes(x = factor(membership_status), y = Total_sale,
    fill = factor(membership_status), label = Total_sale)) +
    geom_bar(stat = "identity", color = "black", width = 0.6) +
    labs(fill = "Membership Status", x = "Membership Status",
        y = "Total Sale", title = "Total Sales by Membership Status") +
    theme_minimal() + scale_fill_manual(values = my_colors) +
    geom_text(aes(label = paste0("£", (scales::comma_format())(Total_sale))),
        position = position_stack(vjust = 0.5), vjust = -0.5,
        size = 4) + scale_y_continuous(labels = scales::dollar_format(prefix = "£",
    suffix = ""))
```

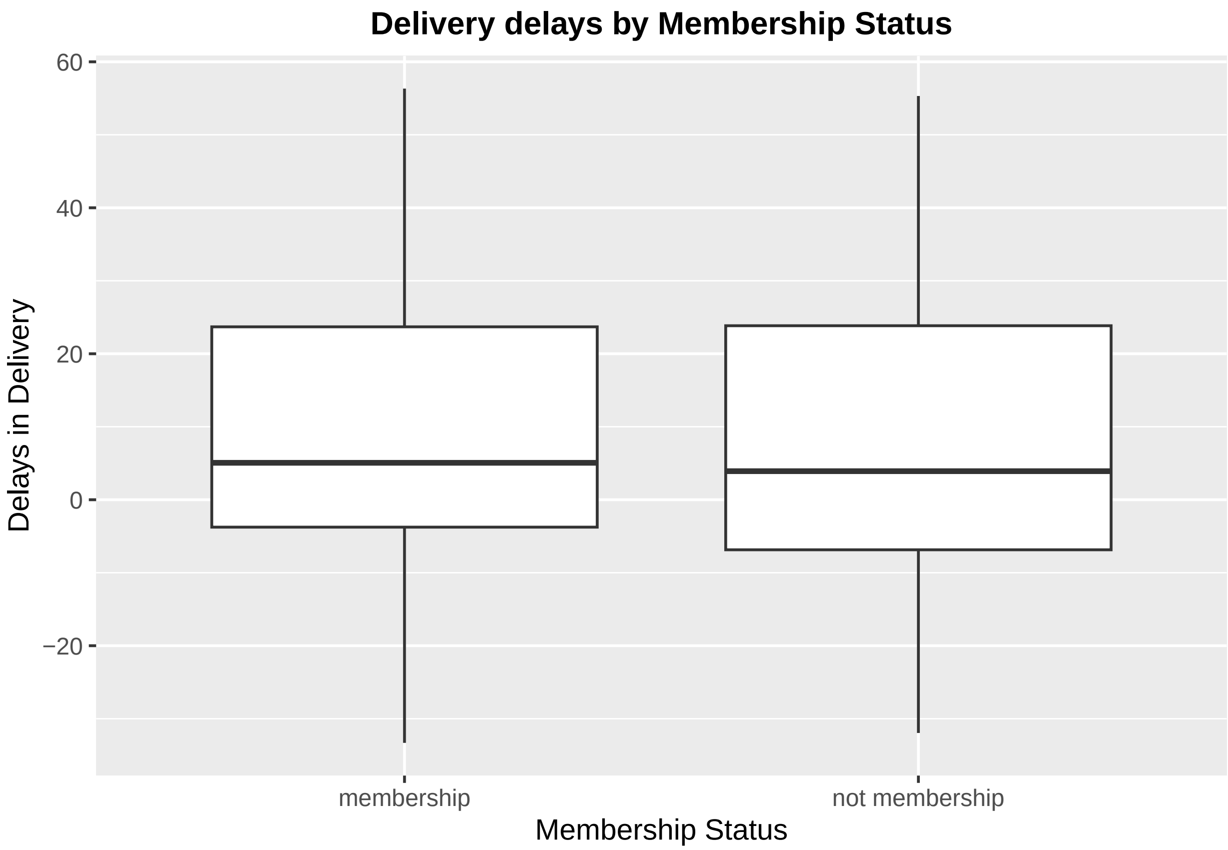


9. Order delay - Membership

Analyzing delivery delays based on customer membership status is essential to ensure fairness and incentivize membership. It's crucial to determine if there are significant differences in delays between members and non-members, as members are typically prioritized. Addressing any disparities promptly is key to maintaining customer satisfaction and encouraging membership uptake.

```
Orderdelay_membership <- dbGetQuery(connection, "
SELECT dd.tracking_number, dd.delay, dt.trans_id, t.order_id, op.customer_id, c.customer_membership
FROM `delivered_deliveries_dataset` AS dd
INNER JOIN `delivery_tracking` AS dt ON dd.tracking_number = dt.tracking_number
INNER JOIN `transaction` AS t ON dt.trans_id = t.trans_id
INNER JOIN `order_products_info` AS op ON t.order_id = op.order_id
INNER JOIN `customer_membership` AS c ON op.customer_id = c.customer_id
")
```

```
ggplot(Orderdelay_membership) + geom_boxplot(aes(x = factor(customer_membership),
    y = delay)) + labs(x = "Membership Status", y = "Delays in Delivery",
    title = "Delivery delays by Membership Status") + theme(plot.title = element_text(size = 12,
    face = "bold", hjust = 0.5))
```



Members appear to experience slightly higher delivery delays, highlighting an area for improvement in our service.

10. Monthly Revenue by City

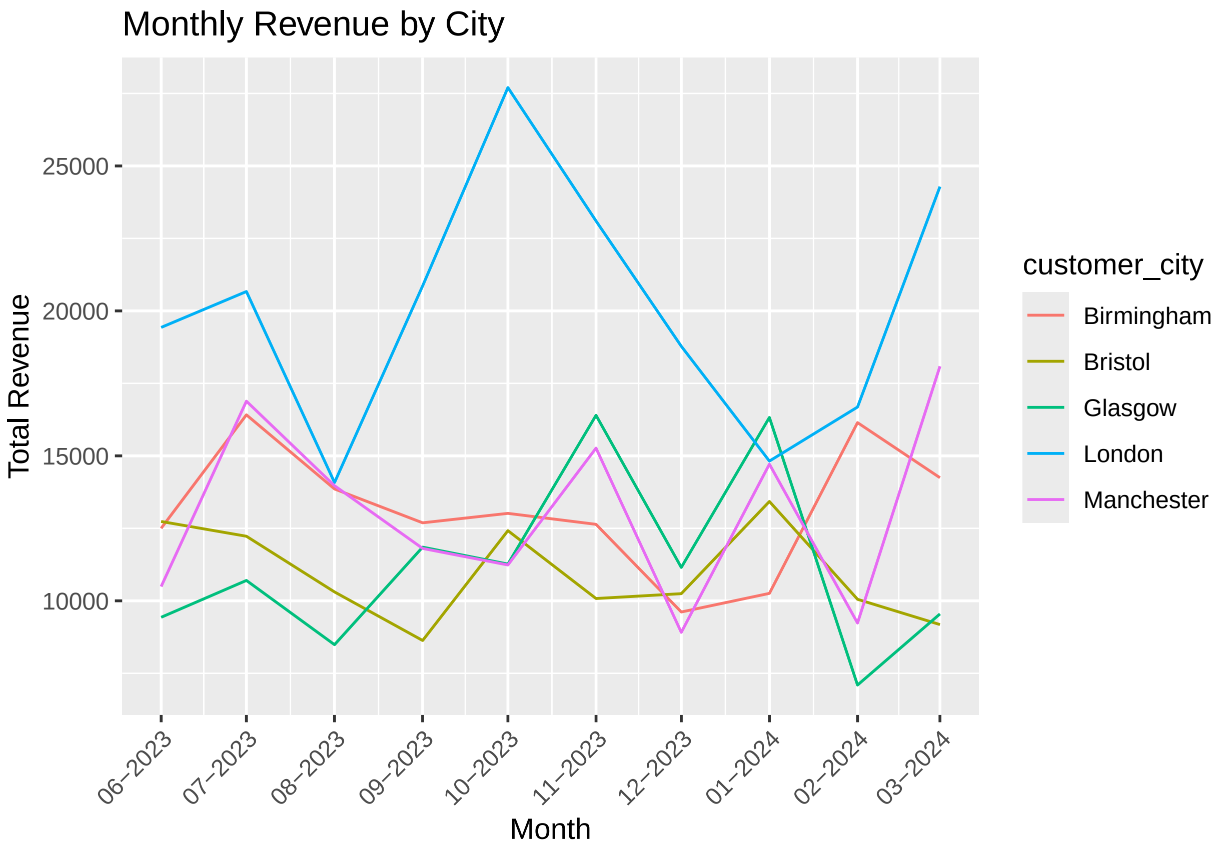
Analyzing monthly revenue by city provides a crucial geographical breakdown, highlighting which cities contribute the most to overall sales and detecting any trend changes over time. This insight aids in strategic marketing targeting and check the effectivness of the resources allocation across different geographical areas.

```
Revenue <- dbGetQuery(connection, "
SELECT o.customer_id, c.customer_city, o.order_id, d.order_date,ROUND(SUM(p.product_price* o.product_qty
FROM 'order_products_info' o, 'product' p, 'promotion' prm, 'customer_basic_info' c, 'customer_membershi
WHERE o.customer_id = m.customer_id AND o.product_id = p.product_id AND c.promo_code = prm.promo_code AN
GROUP BY
    o.order_id;
")
```

```
City_vs_Revenue <- Revenue %>%
    mutate(order_date = as.Date(order_date), month = as.Date(format(order_date,
        "%Y-%m-01"))  # Ensures correct chronological ordering
) %>%
    group_by(customer_city, month) %>%
    summarise(total_revenue_month = sum(revenue), .groups = "drop") %>%
    arrange(customer_city, month)

ggplot(City_vs_Revenue, aes(x = month, y = total_revenue_month,
    group = customer_city, color = customer_city)) + geom_line() +
    labs(title = "Monthly Revenue by City", x = "Month", y = "Total Revenue") +
```

```
    scale_x_date(date_labels = "%m-%Y", date_breaks = "1 month",
        name = "Month") + theme(axis.text.x = element_text(angle = 45,
    hjust = 1))
```



- Overall, there are two peaks across the five cities. One around June of 2023, another one in October of 2023. London seems to consistently have the highest total revenue compared with the other cities. On the contrary, the rest follows a minimum fluctuation across seasons.

11. Top 5 Products by Sales Volume and Total Sales Profit After Discount

The table showcases the top-selling products, elucidating the financial impact of promotions on sales and informing strategic decisions regarding pricing and discount strategies. Additionally, it offers insights into inventory optimization and potential marketing strategies. Lastly, it displays the total profit derived from these products, providing a comprehensive overview of their performance.

```
SELECT p.product_name, SUM(o.product_qty) AS sales_volume, ROUND(SUM(p.product_price* o.product_qty)*(1
FROM "order_products_info" o, "product" p, "promotion" prm, "customer_basic_info" c, "customer_membershi
WHERE o.customer_id = m.customer_id AND o.product_id = p.product_id AND c.promo_code = prm.promo_code AN
GROUP BY p.product_name
ORDER BY total_sales_profit DESC LIMIT 5;
```

Table 30: 5 records

product_name	sales_volume	total_sales_profit
Gentle Micellar Water Makeup Remover	117	3048.38

product_name	sales_volume	total_sales_profit
Flagship Killer Premium Smartphone	69	2924.19
Travel-Friendly Foldable Yoga Mat	89	2861.15
Strategy Masters War Game	69	2554.79
Hydrogel Hydration Booster Moisturizer	53	2487.79

12. Top 5 products sold and percentage discount applied

This table helps us to understand which products have the highest revenue and their performance alongside promotions. These insights are an indication of product offerings and promotional strategies that maximize profitability.

```
SELECT p.product_name, p.category_name, ROUND(SUM(p.product_price* o.product_qty)*(1 - CAST(prm.percenta
FROM "order_products_info" o, "product" p, "promotion" prm, "customer_basic_info" c, "customer_membershi
WHERE o.customer_id = m.customer_id AND o.product_id = p.product_id AND c.promo_code = prm.promo_code AN
GROUP BY p.product_name
ORDER BY revenue DESC LIMIT 5;
```

Table 31: 5 records

product_name	category_name	revenue
Gentle Micellar Water Makeup Remover	Makeup Remover	3048.38
Flagship Killer Premium Smartphone	Smartphone	2924.19
Travel-Friendly Foldable Yoga Mat	Yoga Mat	2861.15
Strategy Masters War Game	Board Games	2554.79
Hydrogel Hydration Booster Moisturizer	Moisturizer	2487.79

13. Top 10 customers that had the highest transaction amount, the percentage discount applied, and which products they bought

This table is generated to identify top-spending customers, evaluate the effectiveness of promotions, and understand product preferences.

```
  SELECT
    o.customer_id,
    o.order_id,
    prm.percentage_discount,
    ROUND(SUM(p.product_price * o.product_qty) * (1 - CAST(prm.percentage_discount AS REAL) / 100) + m.c
  FROM "order_products_info" o
  JOIN "product" p ON o.product_id = p.product_id
  JOIN "customer_basic_info" c ON o.customer_id = c.customer_id
  JOIN "promotion" prm ON c.promo_code = prm.promo_code
  JOIN "customer_membership" m ON c.customer_id = m.customer_id
  GROUP BY o.order_id
  ORDER BY trans_amount DESC
  LIMIT 10
```

Table 32: Displaying records 1 - 10

customer_id	order_id	percentage_discount	trans_amount
DTZ-99095	BQY-6188	5	1947.18
PPP-76997	FYF-2435	10	1811.09
HTW-70988	FME-1994	10	1670.85
HES-57332	TOJ-6235	5	1480.64
FFO-80908	QAU-0445	5	1468.16
VIX-05568	YZQ-5990	20	1463.35
LRT-41739	YDV-3199	5	1430.71
DXQ-32741	XBV-1850	15	1384.39
QGM-02495	OWL-6099	5	1369.88
JDG-70980	HKJ-6958	5	1360.77

14. Supplier sales volume

It shows the top-selling products from the highest-performing suppliers in terms of sales volume. It provides insights into sales volume and supplier performance crucial for inventory management and strategic supplier relationships.

```
SELECT s.supplier_name, p.category_name, p.product_name, SUM(o.product_qty) AS sales_volume
FROM "order_products_info" o, "product" p, "promotion" prm, "customer_basic_info" c, "customer_membershi
WHERE o.customer_id = m.customer_id AND o.product_id = p.product_id AND c.promo_code = prm.promo_code AN
GROUP BY p.supplier_id
ORDER BY sales_volume DESC LIMIT 5;
```

Table 33: 5 records

supplier_name	category_name	product_name	sales_volume
Conn, Feil and Price	Facial Mask	Calming Rosewater Facial Sheet Mask	190
Robel-Johnson	Shorts	Breezy Beachwear Shorts	190
Haag-Gulgowski	Smartwatch	Elegant Rose Gold Fashion Smartwatch	186
Little, Rolfson and DuBuque	Dining Set	Traditional Thanksgiving Dinnerware Collection	185
Pfannerstill-Larson	Makeup Remover	Refreshing Cucumber Makeup Remover Wipes	180

15. Supplier revenue

The table shows the highest revenue achieved by highlighting the product and category name. This is an indication to which suppliers offer the most profitable products within our E-commerce.

```
SELECT s.supplier_name, p.category_name, p.product_name, ROUND(SUM(p.product_price* o.product_qty)*(1 -
FROM "order_products_info" o, "product" p, "promotion" prm, "customer_basic_info" c, "customer_membershi
WHERE o.customer_id = m.customer_id AND o.product_id = p.product_id AND c.promo_code = prm.promo_code AN
GROUP BY p.supplier_id
ORDER BY revenue DESC LIMIT 5;
```

Table 34: 5 records

supplier_name	category_name	product_name	revenue
Haag-Gulgowski	Smartwatch	Elegant Rose Gold Fashion Smartwatch	5956.87
Heidenreich, Hilll and Grimes	Shampoo	Soothing Lavender Chamomile Shampoo	5110.52
Barrows Inc	Router	Dual-Band WiFi Router	4479.57
Robel-Johnson	Shorts	Breezy Beachwear Shorts	4329.33
Denesik and Sons	T-shirt	Striped Pocket Tee Shirt	4310.19

Appendix

Appendix 5.1:

ENTITY: PRODUCT

Attributes	Constraints(NULL or not, P	Data Type	Description	Potential entity linkage
product_id	PRIMARY KEY	INT	Unique identifier for each product.	Suppliers sell product (1:n)
product_name	NOT NULL	VARCHAR(25)	name of the product	Customers purchase orders (1:n)
product_description	NULL	VARCHAR(255)	description of the product	Purchase order line items product (n:m)
category_name	FOREIGN KEY	VARCHAR(25)	which category product belong to	Many products belongs to many categories (m:n)
product_weight	NOT NULL	NUMERIC	product weight (in grams)	categories have hierarchy
product_length	NOT NULL	NUMERIC	product length (in cm)	
product_height	NOT NULL	NUMERIC	product height (in cm)	
product_width	NOT NULL	NUMERIC	product width (in cm)	
product_price	NOT NULL	NUMERIC	product price (in GBP)	
supplier_id	FOREIGN KEY	INT	Unique ID of supplier	

Add-ons | Product | Product Category | Customer | address | Suppliers | Delivery_Shipment | Transaction | Promotion | Orders | Tracking detail | Return | Review | Cart | Reference

Appendix 5.2:

```
library(dplyr)
library(readr)
library(lubridate)
library(hms)

Import data
order_df <- read_csv("order.csv")
delivery_df <- read_csv("Delivery.csv")
trans_df <- read_csv("Transaction.csv")
promotion_df <- read_csv("Promotion.csv")

str(order_df)
str(delivery_df)
str(trans_df)
str(promotion_df)

#remove date and time
```

```
order_df <- order_df[, !names(order_df) %in% c("order_date", "order_time")]
trans_df <- trans_df[,names(trans_df) %in% c("trans_id", "order_id")]
delivery_df <- delivery_df[,!names(delivery_df) %in% c("estimated_delivery_date","estimated_delivery_ti

#Create new date master dataframe with order id as key
unique_orderid <- unique(order_df$order_id)
df_master_date <- data.frame(order_id = unique_orderid)
#asign n value for date and time generator
n = length(unique_orderid)

Date and time generator function
#Generate Date
# Function to generate random dates within a range
generate_random_date <- function(start_date, end_date, n) {
  start_date <- as.Date(start_date)
  end_date <- as.Date(end_date)
  random_dates <- sample(seq(start_date, end_date, by = "day"), n,replace = TRUE)
  return(random_dates)
}

# Generate random times for whole table
generate_random_time <- function(n) {
  hours <- sample(0:23, n, replace = TRUE)
  minutes <- sample(0:59, n, replace = TRUE)
  seconds <- sample(0:59, n, replace = TRUE)
  random_times <- sprintf("%02d:%02d:%02d", hours, minutes, seconds)
  return(random_times)
}
# Generate random times for each row
rand_time <- function(min_hour = 0, max_hour = 23) {
  hours <- sample(min_hour:max_hour, 1)
  minutes <- sample(0:59, 1)
  seconds <- sample(0:59, 1)
  random_time <- sprintf("%02d:%02d:%02d", hours, minutes, seconds)
  return(random_time)}

#random time from initial columns
add_random_time <- function(time_values_column, min_hours = 0, max_hours = 6,min_minutes = 0, max_minut

if (!is.null(seed)) {
set.seed(seed)  # Set the seed for reproducibility
  }

  # Convert time values to POSIXct format
  time_values_posix <- as.POSIXct(time_values_column, format = "%H:%M:%S")


  # Generate random values for hours, minutes, and seconds
  random_hours <- sample(min_hours:max_hours, length(time_values_column), replace = TRUE)
  random_minutes <- sample(min_minutes:max_minutes, length(time_values_column), replace = TRUE)
  random_seconds <- sample(min_seconds:max_seconds, length(time_values_column), replace = TRUE)

  # Add random values to the time values
  new_time_values_posix <- time_values_posix +
```

```
                          random_hours * 3600 +
                          random_minutes * 60 +
                          random_seconds

  # Convert the new time values back to the desired format
  new_time_values <- format(new_time_values_posix, format = "%H:%M:%S")


  return(new_time_values)
}
```

Genearate Data

```
#random date
set.seed(30)
start_date <- "2023-06-01" #set start date
end_date <- "2024-03-31"  #set end date
random_dates <- generate_random_date(start_date, end_date, n)
#put date into data frame
df_master_date<- df_master_date%>% mutate(order_date = random_dates)

#randomtime
set.seed(30)
random_times <- generate_random_time(n)
#put date into data frame
df_master_date<- df_master_date%>% mutate(order_time = random_times)
```

Adjust master date_table

```
# add transaction time, assume customer pay with in 3 hours
df_master_date <- df_master_date %>% mutate(trans_date = order_date)
df_master_date <- df_master_date %>% mutate(trans_time = add_random_time(order_time,max_hours = 2,seed

df_master_date$order_time <- as_hms(df_master_date$order_time)
df_master_date$trans_time <- as_hms(df_master_date$trans_time)

#check if payment are done over midnight if yes trans_date will be next day
for (i in 1:nrow(df_master_date)) {
  if (as.POSIXct(df_master_date$trans_time[i]) < as.POSIXct(df_master_date$order_time[i])) {
    df_master_date$trans_date[i] <- as.Date(df_master_date$trans_date[i]) + 1
  }
}

#check if formula is working
check_master_date <- df_master_date %>% filter(order_date != trans_date)
```

Input date and time back to original df

```
#order table
#match date
master_ord_select <- df_master_date[c("order_id","order_date","order_time")]
m_order<- merge(order_df,master_ord_select,by.x = "order_id",by.y = "order_id",all.x = TRUE)
```

```
#trans table
master_trans_select <- df_master_date[c("order_id","trans_date","trans_time")]
m_tran <- merge(trans_df,master_trans_select,by.x = "order_id",by.y = "order_id",all.x = TRUE)


#Delivery table
m_tran_select <- m_tran[c("trans_id","trans_date","trans_time")]
m_delivery <- merge(delivery_df,m_tran_select,by.x = "trans_id",by.y = "trans_id",all.x = TRUE)
```

Delivery table

```
#New function to random day
random_days <- function(min_range, max_range) {
 sample(min_range:max_range, 1)
 }

#estimate delivery date
m_delivery$estimated_delivery_date <- as.Date(ifelse(m_delivery$shipment_method == "next day",m_delivery
                                                    ifelse(m_delivery$shipment_method == "express",m_del
                                                           ifelse(m_delivery$shipment_method == "standa
#estimate delivery time
m_delivery$estimated_delivery_time <- as_hms(sapply(1:nrow(m_delivery), function(x) rand_time(min_hour =


#actual delivery date
random_days_for_rows <- sapply(1:nrow(m_delivery), function(row) {
  if (m_delivery$shipment_method[row] %in% c("next day")) {
    return(random_days(0, 1))
  } else if (m_delivery$shipment_method[row] == "express") {
    return(random_days(-1, 1))
  } else if (m_delivery$shipment_method[row] == "standard") {
    return(random_days(-1, 2))
  } else {
    return(NA)
  }
})
m_delivery$actual_delivery_date <- as.Date(m_delivery$estimated_delivery_date + random_days_for_rows)


#actual delivery time
m_delivery$actual_delivery_time <-as_hms(sapply(1:nrow(m_delivery), function(x) rand_time(min_hour = 7,

#Delivered Status
#clear previous value
m_delivery$tracking_status <- NA
#define function
random_statuses <- function() {
  statuses <- c("In process", "Dispatch", "Out For Delivery","Delivered")  # Define the possible status
  return(sample(statuses, 1))  # Randomly select one status
}
## Store Value
random_status_for_rows <- sapply(1:nrow(m_delivery), function(row) {
  if (m_delivery$estimated_delivery_date[row] < as.Date("2024-03-01")) {
    return("Delivered")
```

```
    } else {random_statuses()
    }})
#add to table
m_delivery$tracking_status <- random_status_for_rows


#Deleted actual delivered data & time for undelivered item
m_delivery$actual_delivery_date <- as.Date(ifelse(m_delivery$tracking_status != "Delivered",NA,m_delive
m_delivery$actual_delivery_time <- as_hms(ifelse(m_delivery$tracking_status != "Delivered",NA,m_delivery

Promotion Table
#Insert Promotion Start Date
rnum <- nrow(promotion_df)
set.seed(15)
random_dates <- generate_random_date(start_date, end_date, rnum)
#put date into data frame
promotion_df$promo_start_date <- random_dates

#Promotion Expiry Date
random_days_for_rows <- sapply(1:nrow(promotion_df), function(row) {
      return(random_days(90, 180)) }
 )
promotion_df$promo_expire_date <- as.Date(promotion_df$promo_start_date + random_days_for_rows)

nrow(promotion_df %>% filter(promo_expire_date <= promo_start_date))


Finalize Table
f_deliver <- m_delivery[,c("tracking_number","shipment_method","tracking_status","estimated_delivery_da
f_order <- m_order[,c("cutomer_id","order_id","product_id","product_qty","order_date","order_time")]
f_trans <- na.omit(m_tran[,c("trans_id","order_id","trans_date","trans_time")])
f_promotion <- promotion_df

Save file as CSV
write.csv(f_order, file = "data_for_upload/order.csv", row.names = FALSE)
write.csv(f_deliver, file = "data_for_upload/deliver.csv", row.names = FALSE)
write.csv(f_trans, file = "data_for_upload/transaction.csv", row.names = FALSE)
write.csv(f_promotion, file = "data_for_upload/promotion.csv", row.names = FALSE)
```