

# **Small Errors, Big Consequences: Lessons from Data Mismanagement in Business**

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## **Why Small Errors Matter**

- Data drives decisions in production, hiring, marketing & forecasting
- Most business data failures are not dramatic bugs
- They come from tiny, unnoticed mistakes
- If the data is wrong, the decision is wrong
- RStudio does not warn when results are logically wrong

## What Counts as a “Small Error”?

Error	What it Means
“Mexico” vs “México”	R treats them as two different categories
Number stored as text	Math doesn’t work the way we expect
Missing values	Averages and totals become wrong
Duplicate rows	Customers or employees counted twice
Wrong join	Rows multiply or disappear silently

## Tiny Errors, Big Consequences

Area	Tiny Error	Big Result
Retail	Missing value in sales	Too little production that leads to lost on sales
HR	Employee duplicated during merge	Over-hired people that leads to unnecessary cost
Marketing	Duplicated customers	Overspent on ads

## Bad Practice vs Good Practice

*Scenario:*

What is the average purchase amount of customers under 30, and how does it differ by location?

- Click to download dataset: CSV shopping\_behavior dataset

## Bad Practice Example

```
# BAD import: let R guess names and types
data_bad <- read.csv("shopping_behavior.csv")

# BAD filter (forgetting to handle NA)
young_bad <- data_bad[data_bad$Age < 30, ]

# BAD join using merge() with the same location_info
location_info <- data.frame(
  Location = c("California", "New York", "Texas", "Florida"),
  Region   = c("West", "East", "South", "South"),
  stringsAsFactors = FALSE
```

```

)

merged_bad <- merge(young_bad, location_info)

# BAD summary: mean without na.rm and no cleaning of Location variants
result_bad <- aggregate(Purchase.Amount..USD. ~ Location, data = merged_bad, FUN = mean)

# Rename columns to match good version later
names(result_bad) <- c("Location_clean", "avg_spend_bad")
result_bad$avg_spend_bad <- round(result_bad$avg_spend_bad, 2)

result_bad
print(result_bad, n = Inf)
View(result_bad)

```

## Outcome

```

# BAD import: let R guess names and types
data_bad <- read.csv("shopping_behavior.csv")

# BAD filter (forgetting to handle NA, using base [] correctly this time but no cleaning)
young_bad <- data_bad[data_bad$Age < 30, ]

# BAD join using merge() with the same location_info
location_info <- data.frame(
  Location = c("California", "New York", "Texas", "Florida"),
  Region   = c("West", "East", "South", "South"),
  stringsAsFactors = FALSE
)

merged_bad <- merge(young_bad, location_info)

# BAD summary: mean without na.rm and no cleaning of Location variants
result_bad <- aggregate(Purchase.Amount..USD. ~ Location, data = merged_bad, FUN = mean)

# Rename columns to match good version later
names(result_bad) <- c("Location_clean", "avg_spend_bad")
result_bad$avg_spend_bad <- round(result_bad$avg_spend_bad, 2)

# Bad practice result
library(knitr)
library(kableExtra)

```

Table 3: Bad practice result

Location_clean	avg_spend_bad
California	66.30
Florida	53.33
New York	67.23
Texas	55.88

```
result_bad |>
  kbl(caption = "Bad practice result") |>
  scroll_box(height = "600px")
```

## Plot

```
# BAD plot result
barplot(
  result_bad$avg_spend_bad,
  names.arg = result_bad$Location,
  main = "Average Spend (BAD PRACTICE)",
  xlab = "Location",
  ylab = "Average Spend (USD)"
)
```

## Plot Outcome

```
# BAD plot result
barplot(
  result_bad$avg_spend_bad,
  names.arg = result_bad$Location,
  main = "Average Spend (BAD PRACTICE)",
  xlab = "Location",
  ylab = "Average Spend (USD)"
)
```

## Average Spend (BAD PRACTICE)



## Good Practice Example

```
# Example of a good practice
# 1) Import packages
library(dplyr)
library(lubridate)
library(ggplot2)

# 2) Read data with good practices
data_good <- read.csv(
  "shopping_behavior.csv",
  stringsAsFactors = FALSE,
  check.names = FALSE  # keeps "Purchase Amount (USD)" as-is
)

# 3) Parse dates correctly
data_good <- data_good %>%
  mutate(
    Date_good = dmy(Date)
  )

# 4) Remove exact duplicate rows (we know we injected some)
data_nodup <- data_good %>%
  distinct(.keep_all = TRUE)
```

```

# 5) Keep only customers under 30
young_good <- data_nodup %>%
  filter(Age < 30)

# 6) Location lookup table (regions are just for context)
location_info <- data.frame(
  Location = c("California", "New York", "Texas", "Florida"),
  Region    = c("West", "East", "South", "South"),
  stringsAsFactors = FALSE
)

# 7) Safe join: keep all young customers, add Region if Location matches
merged_good <- young_good %>%
  left_join(location_info, by = "Location")

# 8) Clean up Location variants into one standard name
final_clean <- merged_good %>%
  mutate(
    Location_clean = case_when(
      Location %in% c("California", "california", "Californi", "CA") ~ "California",
      Location %in% c("New York", "NewYork", "N. York") ~ "New York",
      TRUE ~ Location
    )
  ) %>%
  group_by(Location_clean) %>%
  summarise(
    avg_spend_young = mean(`Purchase Amount (USD)`, na.rm = TRUE),
    n_customers     = n(),
    .groups = "drop"
  ) %>%
  arrange(Location_clean)

# 9) Round numbers to make the table nice for printing
final_clean$avg_spend_young <- round(final_clean$avg_spend_young, 2)

# 10) Print final result nicely
final_clean

print(final_clean, n = Inf)
View(final_clean)

```

## Outcome

```
# Example of a good practice  
# 1) Import packages  
library(dplyr)
```

Attaching package: 'dplyr'

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

group\_rows

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

filter, lag

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

intersect, setdiff, setequal, union

```
library(lubridate)
```

Attaching package: 'lubridate'

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

date, intersect, setdiff, union

```
library(ggplot2)
```

Warning: package 'ggplot2' was built under R version 4.5.2

```
# 2) Read data with good practices  
data_good <- read.csv(  
  "shopping_behavior.csv",  
  stringsAsFactors = FALSE,  
  check.names = FALSE  # keeps "Purchase Amount (USD)" as-is  
)
```

```

# 3) Parse dates correctly
data_good <- data_good %>%
  mutate(
    Date_good = dmy(Date)
  )

Warning: There was 1 warning in `mutate()` .
i In argument: `Date_good = dmy(Date)` .
Caused by warning:
! 2 failed to parse.

# 4) Remove exact duplicate rows (we know we injected some)
data_nodup <- data_good %>%
  distinct(.keep_all = TRUE)

# 5) Keep only customers under 30
young_good <- data_nodup %>%
  filter(Age < 30)

# 6) Location lookup table (regions are just for context)
location_info <- data.frame(
  Location = c("California", "New York", "Texas", "Florida"),
  Region    = c("West", "East", "South", "South"),
  stringsAsFactors = FALSE
)

# 7) Safe join: keep all young customers, add Region if Location matches
merged_good <- young_good %>%
  left_join(location_info, by = "Location")

# 8) Clean up Location variants into one standard name
final_clean <- merged_good %>%
  mutate(
    Location_clean = case_when(
      Location %in% c("California", "california", "Californi", "CA") ~ "California",
      Location %in% c("New York", "NewYork", "N. York")           ~ "New York",
      TRUE ~ Location
    )
  ) %>%
  group_by(Location_clean) %>%
  summarise(
    avg_spend_young = mean(`Purchase Amount (USD)`, na.rm = TRUE),
    n_customers     = n(),
    .groups = "drop"
  )

```

```

) %>%
arrange(Location_clean)

# 9) Round numbers to make the table nice for printing
final_clean$avg_spend_young <- round(final_clean$avg_spend_young, 2)

# 10) Print final result nicely
final_clean

# A tibble: 50 x 3
  Location_clean avg_spend_young n_customers
  <chr>                <dbl>        <int>
1 Alabama             52.2          20
2 Alaska              66.9          18
3 Arizona             65.5          12
4 Arkansas            67.4          19
5 California          66.1          25
6 Colorado             58.4          13
7 Connecticut         54.7          15
8 Delaware            59.8          11
9 Florida              53.3          15
10 Georgia             52.8          20
# i 40 more rows

```

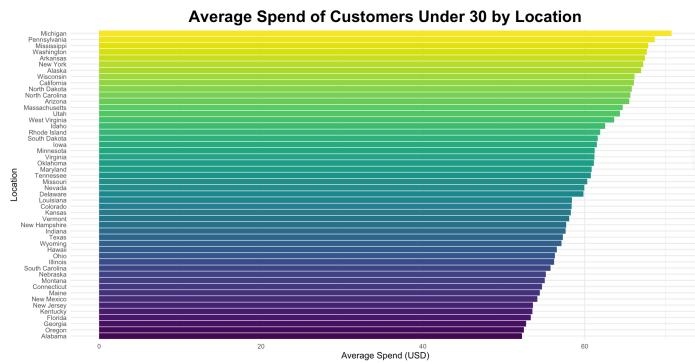
## Plot

```

# 11) Plot final results
ggplot(plot_data, aes(x = Location_clean, y = avg_spend_young, fill = Location_clean)) +
  geom_bar(stat = "identity", show.legend = FALSE) +
  coord_flip() +
  labs(
    title = "Average Spend of Customers Under 30 by Location",
    x = "Location",
    y = "Average Spend (USD)"
  ) +
  scale_fill_viridis_d() +
  theme_minimal() +
  theme(
    plot.title = element_text(face = "bold", size = 20, hjust = 0.5),
    axis.text.y = element_text(size = 8),
    axis.text.x = element_text(size = 8)
  )

```

## Plot Outcome



## Lessons from Data Mismanagement in Business

1. A *tiny mistake* in data can cause a **huge mistake** in a business decision.
2. RStudio won't warn you when the result is *wrong*, only when the **code** is.
3. Never *assume* the data is clean, always **check it**.
4. Good analysis starts **before** modeling with data validation.
5. *Being explicit* in your code **prevents disasters**.
  
6. Documentation and reproducible scripts **protect** you from *mistakes*.
7. *Joins* are one of the most dangerous operations, **check them twice**.
8. **Data types** matter more than most people realize.
9. *Peer review* is **essential**.
10. *Great analysts aren't those who make no mistakes, they are the ones who catch mistakes early.*