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

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Figure 1

Why Smalls 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

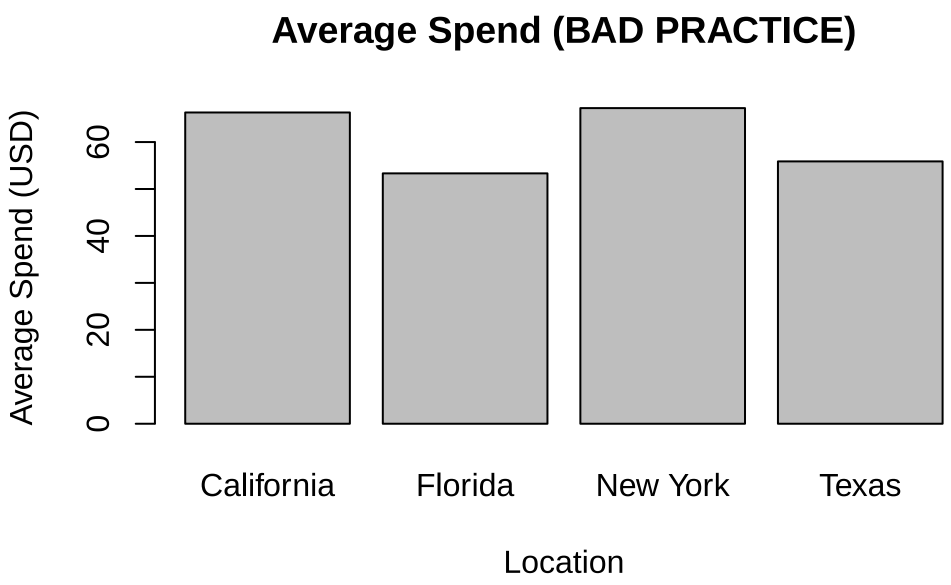
```
result_bad |>
  kbl(caption = "Bad practice result") |>
  scroll_box(height = "600px")
```

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)"
)
```



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)
```

```r
# 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

```r
# 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
```

```r
library(lubridate)
```

```
Attaching package: 'lubridate'

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

    date, intersect, setdiff, union
```

```r
library(ggplot2)
```

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

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

```r
# 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.
```

```r
# 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 |>
  kbl(caption = "Good practice result") |>
  scroll_box(height = "600px")
```

Plot

```
# 11) Plot final results
plot_data <- final_clean %>%
  arrange(avg_spend_young) %>%
  mutate(Location_clean = factor(Location_clean, Location_clean))

ggplot(plot_data, aes(x = Location_clean, y = avg_spend_young)) +
  geom_bar(stat = "identity") +
  coord_flip() +
  labs(
    title = "Average Spend of Customers Under 30 by Location",
    x = "Location",
    y = "Average Spend (USD)"
  ) +
  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

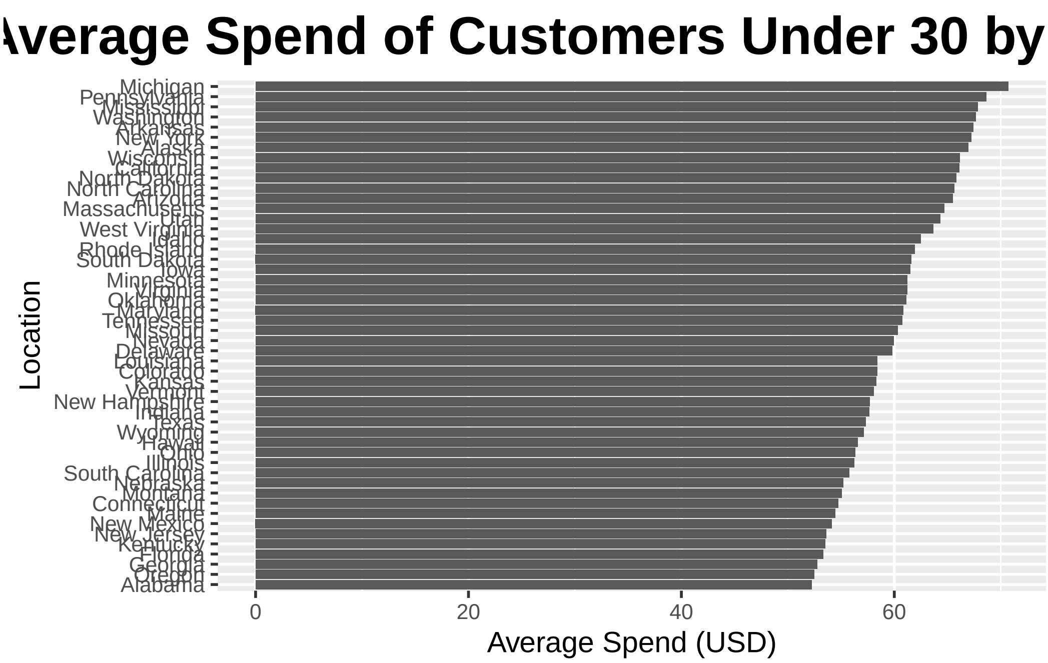
```
# 11) Plot final results
plot_data <- final_clean %>%
  arrange(avg_spend_young) %>%
  mutate(Location_clean = factor(Location_clean, Location_clean))

ggplot(plot_data, aes(x = Location_clean, y = avg_spend_young)) +
```

Table 4: Good practice result

Location_clean	avg_spend_young	n_customers
Alabama	52.25	20
Alaska	66.94	18
Arizona	65.50	12
Arkansas	67.42	19
California	66.08	25
Colorado	58.38	13
Connecticut	54.73	15
Delaware	59.82	11
Florida	53.33	15
Georgia	52.75	20
Hawaii	56.55	20
Idaho	62.50	18
Illinois	56.21	29
Indiana	57.64	11
Iowa	61.50	20
Kansas	58.29	15
Kentucky	53.52	21
Louisiana	58.40	15
Maine	54.46	25
Maryland	60.86	14
Massachusetts	64.69	13
Michigan	70.71	14
Minnesota	61.21	19
Mississippi	67.83	19
Missouri	60.31	13
Montana	55.05	19
Nebraska	55.18	22
Nevada	59.95	22
New Hampshire	57.69	13
New Jersey	53.58	12
New Mexico	54.14	14
New York	67.23	22
North Carolina	65.65	20
North Dakota	65.80	15
Ohio	56.31	13
Oklahoma	61.14	15
Oregon	52.47	17
Pennsylvania	68.65	26
Rhode Island	61.91	11
South Carolina	55.77	13
South Dakota	61.61	18
Tennessee	60.74	19
Texas	57.30	23
Utah	64.33	15
Vermont	58.06	17
Virginia	61.20	25
Washington	67.67	18
West Virginia	63.65	23
Wisconsin	66.14	14
Wyoming	57.12	16

```r
  geom_bar(stat = "identity") +
  coord_flip() +
  labs(
    title = "Average Spend of Customers Under 30 by Location",
    x = "Location",
    y = "Average Spend (USD)"
  ) +
  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)
  )
```



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.***