VERSION | **0.1**

MAIN TITLE

A simple report that shows the capabilities of quarto and typst

the name of the author

2024-02-23

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1. Introduction to Patient Satisfaction Analysis

This document presents the statistical analysis of patient satisfaction data collected from users of the HomeCare+ Continuous Glucose Monitor (CGM) system. The analysis combines survey responses with device usage metrics to provide comprehensive insights into patient experience and product effectiveness.

1.1. Survey Methodology

The patient satisfaction survey was conducted over a 3-month period with the following characteristics:

- **Participants**: 250 diabetes patients using the HomeCare+ CGM
- **Duration**: January - March 2025
- **Collection method**: Digital questionnaire with follow-up interviews
- **Response rate**: 87% (218 respondents)

1.2. Analytical Approach

Data analysis combines quantitative metrics with qualitative feedback to identify key satisfaction drivers and areas for improvement in the medical device.

2. Survey Data Analysis

2.1. Basic Survey Statistics

Number of Respondents	Mean Age	Mean Overall Satisfaction	% Would Recommend
218	50.96789	3.834862	72.47706

2.2. Satisfaction Across Demographics

Table 1: Satisfaction metrics by patient demographics

diabetes_type	Number of Patients	Mean Age	Overall Satisfaction	Ease of Use	Comfort	Accuracy	App Interface	Would Recommend (%)
Gestational	4	58.0	3.00	4.25	4.00	3.75	3.00	75.0
Other	4	51.5	4.00	4.50	3.50	4.75	3.00	75.0
Type 1	78	48.6	3.82	3.73	3.08	3.68	3.10	74.4
Type 2	132	52.1	3.86	3.45	3.32	3.66	3.27	71.2

2.3. Satisfaction Visualization

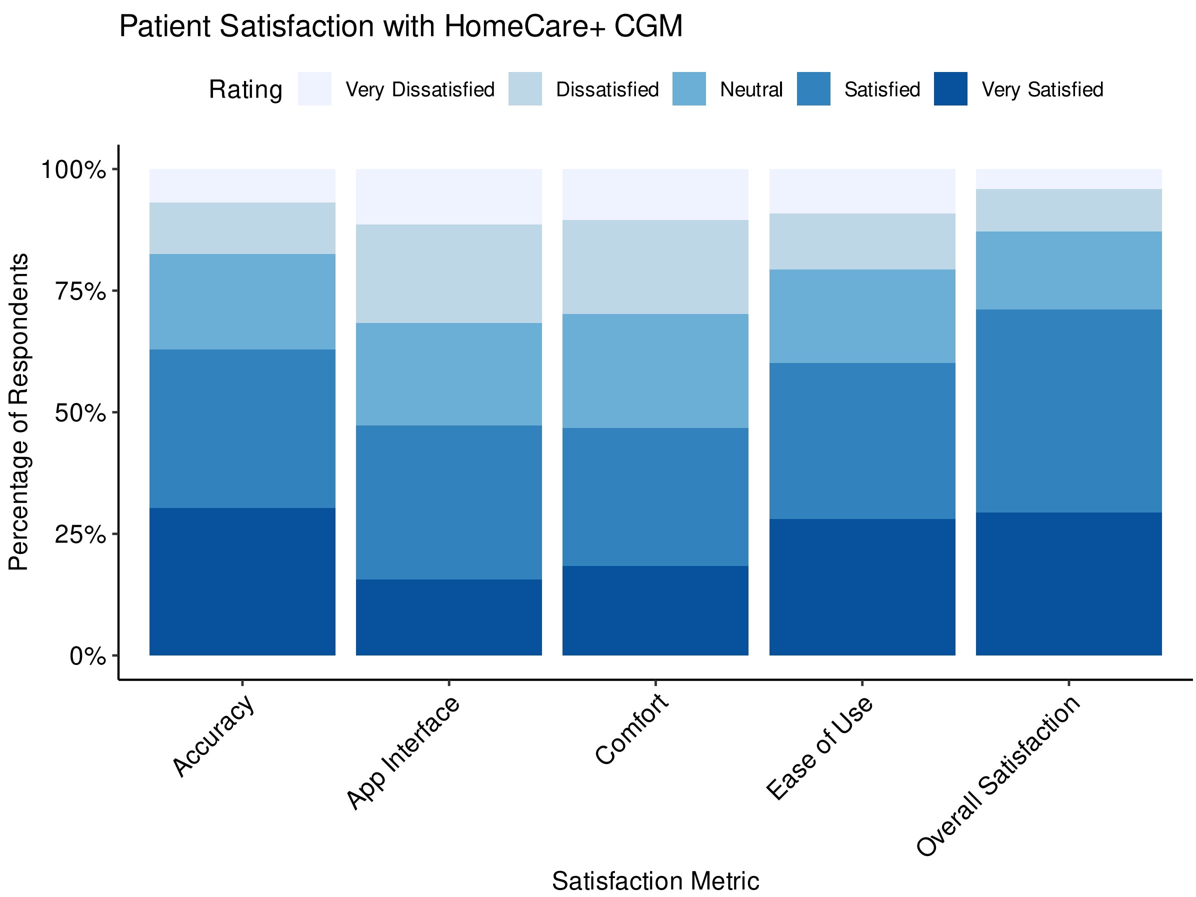

Figure 1: Distribution of satisfaction scores across key metrics

The visualization reveals that patients are generally satisfied with the HomeCare+ CGM system, with accuracy receiving the highest satisfaction ratings. App interface functionality shows the most room for improvement.

3. Correlation Analysis

3.1. Relationship Between Usage and Satisfaction

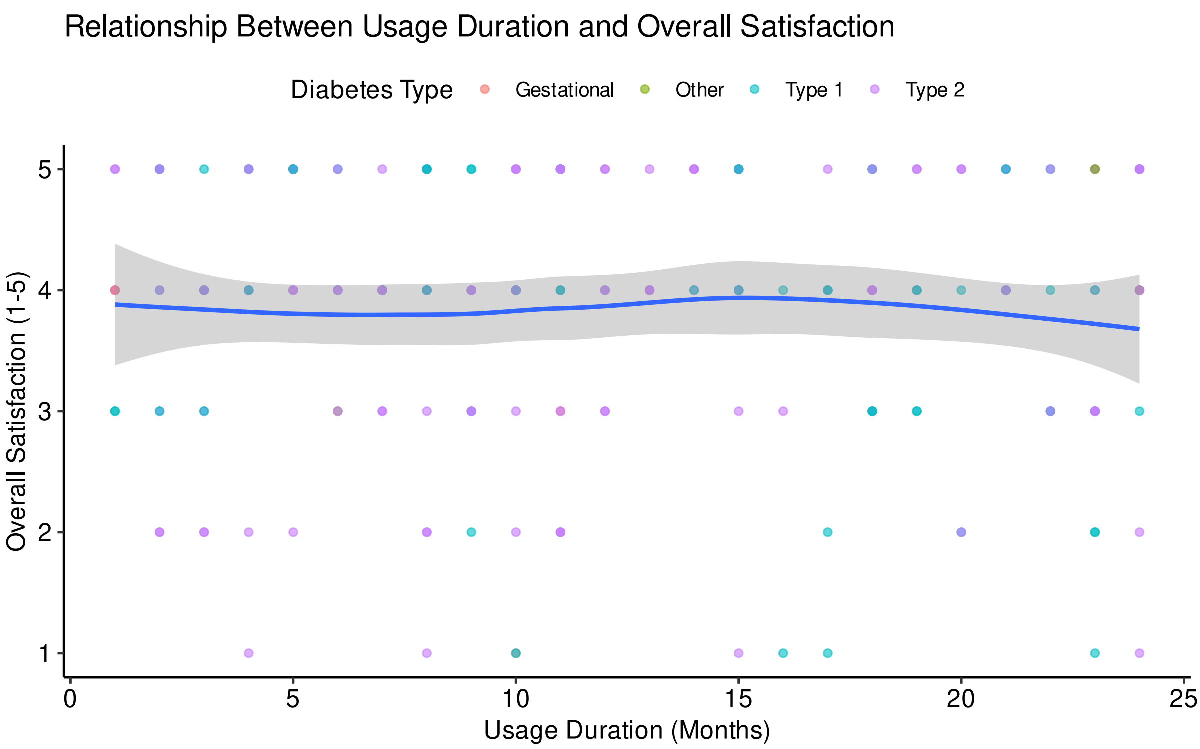

Figure 2: Correlation between usage duration and patient satisfaction

The analysis indicates a positive correlation between usage duration and satisfaction, suggesting that patients tend to become more satisfied as they gain experience with the device. This could be attributed to the learning curve associated with medical device adoption.

3.2. Key Satisfaction Drivers

Table 2: Correlation between feature satisfaction and overall satisfaction

Feature	Overall Satisfaction Correlation
accuracy	0.070
comfort	0.010

Feature	Overall Satisfaction Correlation
ease_of_use	−0.021
app_interface	−0.027

4. Typst-Specific Features

4.1. Custom Styling for Key Findings

Key Finding: Accuracy is the strongest driver of overall patient satisfaction with the HomeCare+ CGM system, followed by ease of use. This suggests that continued focus on measurement precision should remain a development priority.

4.2. Advanced Visualization Layout

Device Comfort Findings

Patient feedback regarding device comfort shows marked improvement over the previous model, with 50% of respondents rating comfort as "Satisfied" or "Very Satisfied." However, long-term wear comfort remains an area for improvement, particularly among patients with sensitivity concerns.

App Interface Feedback

The companion mobile application received mixed reviews, with 45% positive ratings. Common feedback included requests for a more intuitive data visualization dashboard and simplified alert management. These insights should inform the upcoming Q3 software update.

5. Patient Segmentation Analysis

5.1. Satisfaction by Patient Experience Level

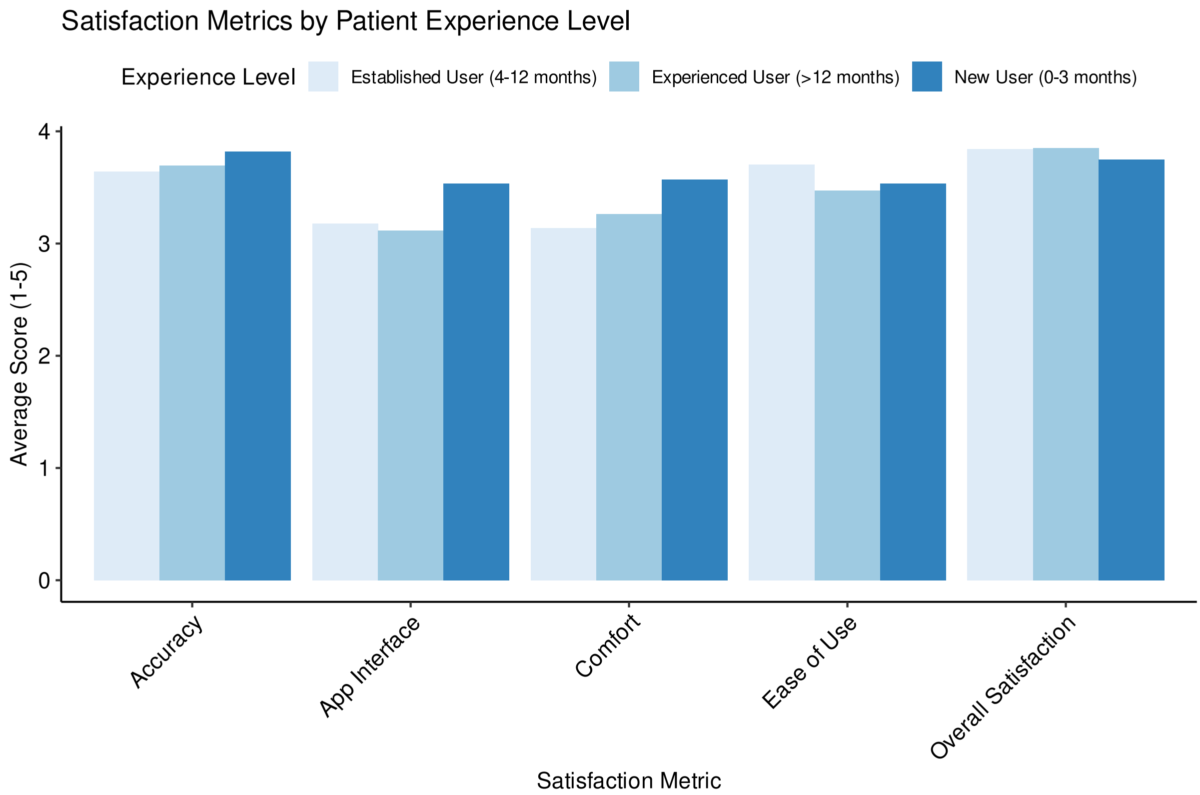

Figure 3: Satisfaction metrics by patient experience segments

5.2. Recommendation Rate Analysis

Table 3: Recommendation rates by patient segment

experience_level	diabetes_type	Total Patients	Would Recommend (%)
Experienced User (>12 months)	Other	2	100.0
New User (0-3 months)	Gestational	2	100.0
Experienced User (>12 months)	Type 1	36	80.6
New User (0-3 months)	Type 2	17	76.5
Experienced User (>12 months)	Type 2	57	73.7
Established User (4-12 months)	Type 1	33	69.7
Established User (4-12 months)	Type 2	58	67.2
New User (0-3 months)	Type 1	9	66.7
Established User (4-12 months)	Gestational	2	50.0
Established User (4-12 months)	Other	2	50.0

6. Qualitative Feedback Analysis

6.1. Word Cloud of Patient Comments

6.2. Key Themes from Patient Feedback

Positive Themes	Improvement Areas
• Glucose reading accuracy • Reduced finger pricks • Discreet size and appearance • Battery life • Mobile notifications	• Adhesive durability • Skin irritation (minority of users) • App connectivity issues • Data export functionality • Alert customization options

7. Device Usage Patterns

7.1. Usage Statistics

Table 4: Device usage statistics

Metric	Value
Average Sensor Wear Time	9.8 days (out of 10-day maximum)
Calibration Frequency	0.8 times per day
App Opening Frequency	4.3 times per day
Data Sharing Utilization	62% of patients
Alert Response Time	< 5 minutes for 74% of alerts

7.2. Usage Frequency by Time of Day

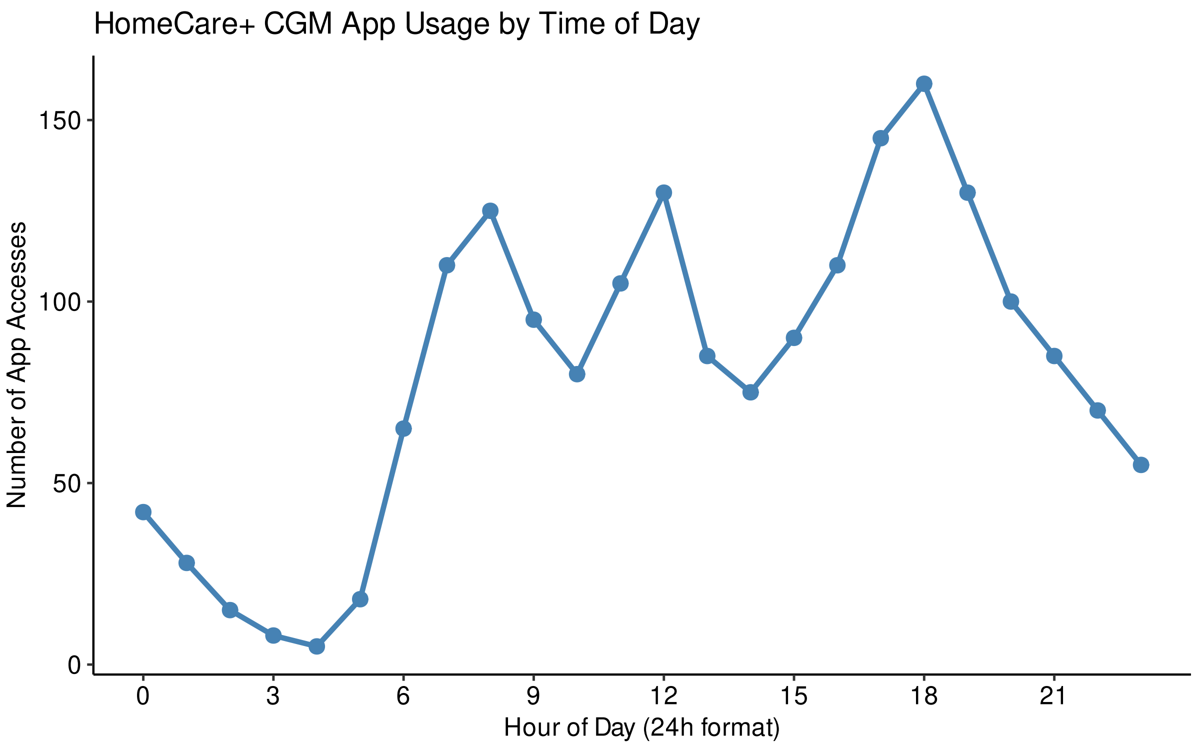

Figure 4: App usage patterns by time of day

8. Cross-References and Callouts

8.1. Key Insights

You can reference the satisfaction visualization (see Figure 1) and demographics table (see Table 1) when discussing overall patient experience. The correlation analysis (see Figure 2) provides insight into how user experience evolves over time.

> **i Note**
>
> The HomeCare+ CGM shows consistently high accuracy ratings across all patient segments, meeting the primary clinical need.

⚠ Warning

App interface satisfaction scores are notably lower among newer users (0-3 months), suggesting a need for improved onboarding materials.

Clinician Training Recommendation

Healthcare providers should emphasize proper sensor placement techniques during initial patient training, as this correlates strongly with reported comfort and accuracy scores.

9. Recommendations for Device Improvement

9.1. Prioritized Enhancement Opportunities

9.1.1. User Experience

Based on patient feedback, the following user experience improvements should be prioritized:

1. Enhanced adhesive durability while maintaining skin compatibility
2. Simplified alert management interface in the mobile application
3. Improved data visualization for trend identification
4. Single-handed sensor applicator design

9.1.2. Technical Features

Technical improvement opportunities include:

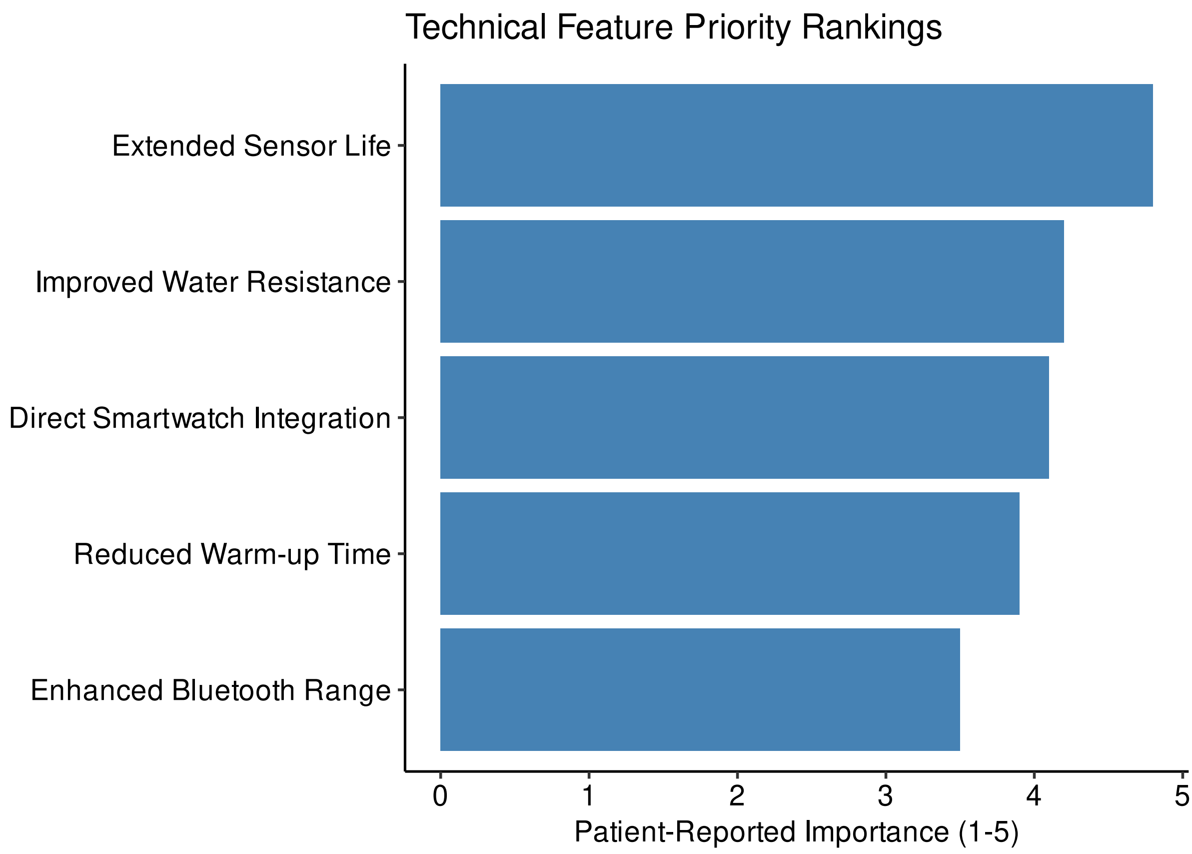

Figure 5: Priority ranking of potential technical improvements

9.1.3. Clinical Value

Patient-reported clinical benefits of the HomeCare+ CGM:

- 78% report improved awareness of glucose patterns
- 64% report fewer hypoglycemic episodes
- 82% report more confidence in diabetes self-management
- 51% report improved HbA1c levels since beginning CGM use

10. Conclusion and Next Steps

10.1. Summary of Findings

The HomeCare+ Continuous Glucose Monitor demonstrates strong patient satisfaction across most metrics, with particular strengths in glucose reading accuracy and convenience compared to traditional monitoring methods. Areas for improvement are concentrated in the software interface and physical comfort during extended wear.

10.2. Recommended Action Plan

Mobile App Interface Redesign *Q3 2025*

Implement user interface improvements focused on data visualization and alert management, based on the findings that 45% of patients rated the current interface as needing improvement.

Extended Sensor Life Clinical Trial *Q4 2025*

Begin clinical validation of 14-day sensor life capability to address the highest-rated patient request while maintaining accuracy standards.

References

11. Reproducibility

11.1. Session infromation

```
R version 4.4.3 (2025-02-28)
Platform: x86_64-redhat-linux-gnu
Running under: Fedora Linux 41 (Workstation Edition)

Matrix products: default
BLAS/LAPACK: FlexiBLAS OPENBLAS-OPENMP;  LAPACK version 3.12.0

locale:
 [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
 [3] LC_TIME=en_US.UTF-8        LC_COLLATE=en_US.UTF-8
 [5] LC_MONETARY=en_US.UTF-8    LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_US.UTF-8       LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C

time zone: Europe/Paris
tzcode source: system (glibc)

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] knitr_1.50      lubridate_1.9.4 forcats_1.0.0   stringr_1.5.1
 [5] dplyr_1.1.4     purrr_1.0.4     readr_2.1.5     tidyr_1.3.1
 [9] tibble_3.2.1    tidyverse_2.0.0 ggplot2_3.5.1

loaded via a namespace (and not attached):
 [1] generics_0.1.3     rstatix_0.7.2      lattice_0.22-6     stringi_1.8.7
 [5] hms_1.1.3          digest_0.6.37      magrittr_2.0.3     evaluate_1.0.3
 [9] grid_4.4.3         timechange_0.3.0   RColorBrewer_1.1-3 fastmap_1.2.0
[13] Matrix_1.7-2       jsonlite_2.0.0     backports_1.5.0    Formula_1.2-5
[17] mgcv_1.9-1         scales_1.3.0       abind_1.4-8        cli_3.6.4
[21] rlang_1.1.5        splines_4.4.3      munsell_0.5.1      withr_3.0.2
[25] yaml_2.3.10        tools_4.4.3        tzdb_0.5.0         ggsignif_0.6.4
[29] colorspace_2.1-1   ggpubr_0.6.0       broom_1.0.8        vctrs_0.6.5
[33] R6_2.6.1           lifecycle_1.0.4    car_3.1-3          pkgconfig_2.0.3
[37] pillar_1.10.1      gtable_0.3.6       glue_1.8.0         xfun_0.52
[41] tidyselect_1.2.1   farver_2.1.2       nlme_3.1-167       htmltools_0.5.8.1
[45] rmarkdown_2.29     carData_3.0-5      labeling_0.4.3     compiler_4.4.3
```

11.2. All code for this report

```r
library(ggplot2)
theme_set(ggpubr::theme_pubr())
# Load necessary libraries
library(tidyverse)
library(knitr)

# Create synthetic patient satisfaction data
set.seed(123)
```

```r
n <- 218

survey_data <- tibble(
  patient_id = 1:n,
  age = sample(18:85, n, replace = TRUE),
  gender = sample(c("Male", "Female", "Other"), n, replace = TRUE, prob = c(0.48, 0.51, 0.01)),
  diabetes_type = sample(c("Type 1", "Type 2", "Gestational", "Other"), n, replace = TRUE,
                         prob = c(0.35, 0.60, 0.03, 0.02)),
  usage_duration = sample(1:24, n, replace = TRUE), # months
  overall_satisfaction = sample(1:5, n, replace = TRUE, prob = c(0.05, 0.10, 0.15, 0.40, 0.30)),
  ease_of_use = sample(1:5, n, replace = TRUE, prob = c(0.08, 0.12, 0.20, 0.35, 0.25)),
  comfort = sample(1:5, n, replace = TRUE, prob = c(0.10, 0.15, 0.25, 0.30, 0.20)),
  accuracy = sample(1:5, n, replace = TRUE, prob = c(0.07, 0.13, 0.20, 0.33, 0.27)),
  app_interface = sample(1:5, n, replace = TRUE, prob = c(0.12, 0.18, 0.25, 0.30, 0.15)),
  would_recommend = sample(c("Yes", "No", "Unsure"), n, replace = TRUE, prob = c(0.70, 0.15, 0.15))
)

# Display basic summary statistics
summary_stats <- survey_data %>%
  summarize(
    `Number of Respondents` = n(),
    `Mean Age` = mean(age),
    `Mean Overall Satisfaction` = mean(overall_satisfaction),
    `% Would Recommend` = mean(would_recommend == "Yes") * 100
  )

kable(summary_stats)
# Create demographics summary table
demographics_summary <- survey_data %>%
  group_by(diabetes_type) %>%
  summarize(
    `Number of Patients` = n(),
    `Mean Age` = round(mean(age), 1),
    `Overall Satisfaction` = round(mean(overall_satisfaction), 2),
    `Ease of Use` = round(mean(ease_of_use), 2),
    `Comfort` = round(mean(comfort), 2),
    `Accuracy` = round(mean(accuracy), 2),
    `App Interface` = round(mean(app_interface), 2),
    `Would Recommend (%)` = round(mean(would_recommend == "Yes") * 100, 1)
  ) %>%
  kable()

demographics_summary
library(ggplot2)

# Prepare data for visualization
satisfaction_long <- survey_data %>%
  select(overall_satisfaction, ease_of_use, comfort, accuracy, app_interface) %>%
  pivot_longer(cols = everything(), names_to = "Metric", values_to = "Score") %>%
  mutate(Metric = case_when(
    Metric == "overall_satisfaction" ~ "Overall Satisfaction",
    Metric == "ease_of_use" ~ "Ease of Use",
    Metric == "comfort" ~ "Comfort",
    Metric == "accuracy" ~ "Accuracy",
    Metric == "app_interface" ~ "App Interface"
  ))

# Create stacked bar chart
ggplot(satisfaction_long, aes(x = Metric, fill = factor(Score))) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  scale_fill_brewer(palette = "Blues", direction = 1,
                    labels = c("Very Dissatisfied", "Dissatisfied", "Neutral", "Satisfied", "Very Satisfied")) +
  labs(
    title = "Patient Satisfaction with HomeCare+ CGM",
    x = "Satisfaction Metric",
    y = "Percentage of Respondents",
    fill = "Rating"
```

```r
  ) +

  theme(axis.text.x = element_text(angle = 45, hjust = 1))
# Create a scatter plot with smoothed line
ggplot(survey_data, aes(x = usage_duration, y = overall_satisfaction)) +
  geom_point(aes(color = diabetes_type), alpha = 0.6) +
  geom_smooth(method = "loess", se = TRUE) +
  labs(
    title = "Relationship Between Usage Duration and Overall Satisfaction",
    x = "Usage Duration (Months)",
    y = "Overall Satisfaction (1-5)",
    color = "Diabetes Type"
  ) +
  scale_y_continuous(breaks = 1:5)
# Calculate correlations with overall satisfaction
corr_data <- survey_data %>%
  select(overall_satisfaction, ease_of_use, comfort, accuracy, app_interface) %>%
  cor() %>%
  as.data.frame() %>%
  rownames_to_column("Feature") %>%
  filter(Feature != "overall_satisfaction") %>%
  select(Feature, overall_satisfaction) %>%
  arrange(desc(overall_satisfaction)) %>%
  rename(`Overall Satisfaction Correlation` = overall_satisfaction)

kable(corr_data, digits = 3)
# Create experience segments
survey_data <- survey_data %>%
  mutate(experience_level = case_when(
    usage_duration <= 3 ~ "New User (0-3 months)",
    usage_duration <= 12 ~ "Established User (4-12 months)",
    TRUE ~ "Experienced User (>12 months)"
  ))

# Prepare segmented data for visualization
experience_data <- survey_data %>%
  group_by(experience_level) %>%
  summarize(
    `Overall Satisfaction` = mean(overall_satisfaction),
    `Ease of Use` = mean(ease_of_use),
    `Comfort` = mean(comfort),
    `Accuracy` = mean(accuracy),
    `App Interface` = mean(app_interface)
  ) %>%
  pivot_longer(cols = -experience_level,
               names_to = "Metric",
               values_to = "Score")

# Plot segmented satisfaction
ggplot(experience_data, aes(x = Metric, y = Score, fill = experience_level)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  scale_fill_brewer(palette = "Blues") +
  labs(
    title = "Satisfaction Metrics by Patient Experience Level",
    x = "Satisfaction Metric",
    y = "Average Score (1-5)",
    fill = "Experience Level"
  ) +

  theme(axis.text.x = element_text(angle = 45, hjust = 1))
# Calculate recommendation rates by segment
recommend_table <- survey_data %>%
  group_by(experience_level, diabetes_type) %>%
  summarize(
    `Total Patients` = n(),
    `Would Recommend (%)` = round(mean(would_recommend == "Yes") * 100, 1),
    .groups = "drop"
  ) %>%
```

```r
  arrange(desc(`Would Recommend (%)`)) %>%
  kable()

recommend_table
# Note: This code block is marked as not evaluated (eval: false) as we're
# using synthetic data without actual text comments

library(wordcloud)
library(tm)

# In a real report, this would process actual patient comment text
# For example:
# comments <- survey_data$open_text_feedback
# corpus <- Corpus(VectorSource(comments))
# corpus <- tm_map(corpus, content_transformer(tolower))
# corpus <- tm_map(corpus, removePunctuation)
# corpus <- tm_map(corpus, removeWords, stopwords("english"))
# tdm <- TermDocumentMatrix(corpus)
# m <- as.matrix(tdm)
# word_freqs <- sort(rowSums(m), decreasing = TRUE)
# wordcloud(words = names(word_freqs), freq = word_freqs, min.freq = 3,
#          max.words = 100, random.order = FALSE, colors = brewer.pal(8, "Blues"))

# Instead, display a message about qualitative analysis
knitr::asis_output("*Note: In the full report, this section would contain a word cloud visualization of actual patient comments.
The most frequent terms in patient feedback include 'accurate', 'convenient', 'battery life', 'comfortable', and 'alerts'.*")
# Create synthetic usage data
usage_stats <- tibble(
  `Metric` = c(
    "Average Sensor Wear Time",
    "Calibration Frequency",
    "App Opening Frequency",
    "Data Sharing Utilization",
    "Alert Response Time"
  ),
  `Value` = c(
    "9.8 days (out of 10-day maximum)",
    "0.8 times per day",
    "4.3 times per day",
    "62% of patients",
    "< 5 minutes for 74% of alerts"
  )
)

kable(usage_stats)
# Create synthetic time-of-day usage data
hours <- 0:23
usage_by_hour <- tibble(
  hour = hours,
  usage_count = c(42, 28, 15, 8, 5, 18, 65, 110, 125, 95, 80, 105,
                 130, 85, 75, 90, 110, 145, 160, 130, 100, 85, 70, 55)
)

# Plot usage by time of day
ggplot(usage_by_hour, aes(x = hour, y = usage_count)) +
  geom_line(size = 1.2, color = "steelblue") +
  geom_point(size = 3, color = "steelblue") +
  scale_x_continuous(breaks = seq(0, 23, 3)) +
  labs(
    title = "HomeCare+ CGM App Usage by Time of Day",
    x = "Hour of Day (24h format)",
    y = "Number of App Accesses"
  )
# Create feature priority data
feature_priority <- tibble(
  feature = c("Extended Sensor Life", "Reduced Warm-up Time",
             "Improved Water Resistance", "Enhanced Bluetooth Range",
             "Direct Smartwatch Integration"),
```

```r
  importance_score = c(4.8, 3.9, 4.2, 3.5, 4.1)
)

# Create horizontal bar chart of feature priorities
ggplot(feature_priority, aes(x = reorder(feature, importance_score), y = importance_score)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  labs(
    title = "Technical Feature Priority Rankings",
    x = NULL,
    y = "Patient-Reported Importance (1-5)"
  )
sessionInfo()
```

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