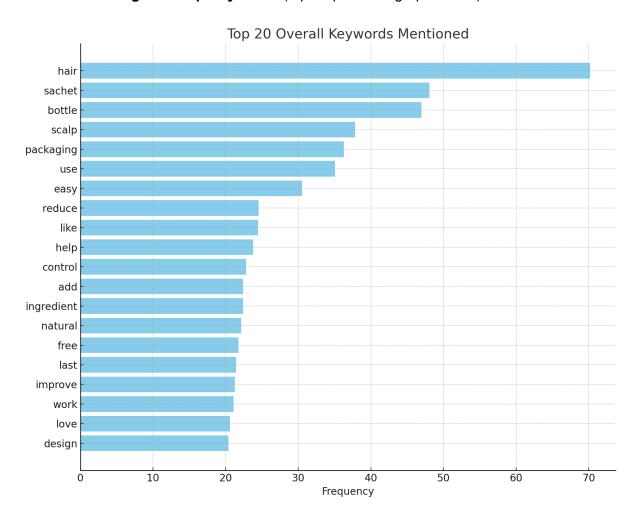
## **Section 15: Keyword & Phrase Extraction**

## **Keyword Tables**

- Overall Top Keywords (top 20)
- Segment Top Keywords (top 10 per demographic slice)



## Insights from the Top 20 Keyword Frequencies Chart:

#### 1. Dominance of 'Hair'-Related Concerns:

 The term "hair" stands out as the most frequently mentioned keyword, indicating that consumers strongly associate the product with hair care benefits and outcomes.

## 2. Packaging Formats are Key Considerations:

 Keywords like "sachet" and "bottle" are highly ranked, highlighting that packaging format significantly influences user preferences and perceptions.

### 3. Scalp and Ingredient-Focused Benefits:

 Words like "scalp," "control," "natural," "ingredient," and "reduce" suggest that many consumers are focused on functional benefits such as dandruff control, scalp health, and natural ingredients.

## 4. Ease of Use and Design Matter:

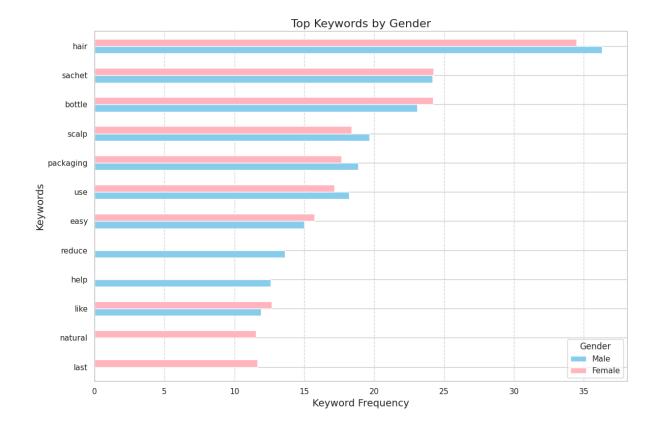
 Terms such as "easy," "use," "design," and "packaging" imply that usability and aesthetic aspects of the product and packaging are important to consumers.

#### 5. Positive Sentiment and Efficacy:

 Keywords like "love," "help," "work," and "improve" reflect overall satisfaction and the perceived effectiveness of the product.

## **Key Phrase Tables**

• Overall Key Phrases (top 10)



## **Insights from Key Phrase Diagram:**

#### 1. High Commonality Between Genders

 "Hair", "sachet", "bottle", "scalp", "packaging", "use", "easy", and "like" are common top keywords for both genders, highlighting shared perceptions and priorities.

## 2. Top Priority: Hair

• Both male (36.30%) and female (34.48%) consumers most frequently mentioned "hair", clearly signaling that product communication and formulation must strongly resonate with hair care benefits.

#### 3. Format Preference: Sachet vs Bottle

• Sachet and bottle keywords score nearly equally for both genders, though sachets have a slightly higher association with female consumers, which could imply convenience preference or trial behavior.

#### 4. Functional Benefits Matter

•	Keywords like "use", "easy", "reduce", and "help" indicate a focus on functional
	value (ease of use, helpfulness, problem-solving).

#### 5. Emotional and Natural Aspects for Women

 Women associate terms like "natural" and "last" more frequently, suggesting durability and natural ingredients play a greater role in female preference.

#### 6. Male Consumers Show Functional Orientation

• Males highlight "reduce" and "help", implying a stronger utility-based outlook (e.g., reduce dandruff, help scalp health).

### 2. Analysis Notebook

- o Documented code for TF-IDF and KeyBERT extraction
- Parameter settings (ngram ranges, stop-word list)

https://colab.research.google.com/drive/18H6BxSEtdJiG19SZo6dnLsH2uL0OXTDE#scrollTo =PUlourInittl

# Description

## Section 15: Keyword & Phrase Extraction

**Scope:** Extract meaningful words and short phrases from open-ended responses to support summarization, topic modeling, and segment-specific insights.

## **Objectives**

- Extract the most informative keywords and phrases from Q19–Q21, Q25–Q26, Q28–Q29, Q33, and Q40–Q41.
- Enable targeted summarization and segmentation-based language insights.
- Surface unique terms used by demographic cohorts (Age, Gender, NCCS).

# **Analysis Tasks**

Task	Details	Method
1. Text Collectio n	- Combine open-end ed responses from questions Q19–Q21, Q25–Q26, Q28–Q29, Q33, Q40–Q41 Include responde nt metadata: Gender, Age, NCCS.	<pre>python import pandas as pd df = pd.read_csv("open_ended_data.csv") # Filter and combine relevant questions columns_to_use = ['Q19', 'Q20', 'Q21', 'Q25', 'Q26', 'Q28', 'Q29', 'Q33', 'Q40', 'Q41'] df['Combined_Text'] = df[columns_to_use].fillna('').agg(' '.join, axis=1) df_text = df[['Respondent_ID', 'Combined_Text', 'Gender', 'Age', 'NCCS']]</pre>
2. Preproce ssing	Lowercas e, remove punctuatio n, stop words.  Optionally lemmatize .	<pre>python import spacy nlp = spacy.load("en_core_web_sm", disable=["parser", "ner"]) def preprocess(text): doc = nlp(text.lower()) tokens = [token.lemma_ for token in doc if not token.is_stop and token.is_alpha] return " ".join(tokens) df_text["Clean_Text"] = df_text["Combined_Text"].apply(preprocess)</pre>

```
3. TF-IDF
                    python from sklearn.feature_extraction.text
Extractio
          Calculate
                    import TfidfVectorizer tfidf =
          TF-IDF
n
                    TfidfVectorizer(ngram_range=(1, 2),
          scores for
                    max_features=5000) tfidf_matrix =
          unigrams
                    tfidf.fit_transform(df_text["Clean_Text"])
          and
                    tfidf_df = pd.DataFrame(tfidf_matrix.toarray(),
          bigrams.
                    columns=tfidf.get_feature_names_out())
         - Identify
         top
                    top_keywords =
          keywords
                    tfidf_df.mean().sort_values(ascending=False).hea
          globally
                    d(20)
          and by
          segment.
         - Use a
4.
                    python from keybert import KeyBERT kw_model =
KeyBERT
         Sentence-
                    KeyBERT(model="all-MiniLM-L6-v2") def
Phrase
          BERT
                    extract_phrases(text): return
Extractio
          model via
                    kw_model.extract_keywords(text,
          KeyBERT.
n
                    keyphrase_ngram_range=(2, 3),
         - Extract
                    stop_words="english", top_n=5)
         top key
                    df_text["Key_Phrases"] =
          phrases
          (2-3)
                    df_text["Clean_Text"].apply(lambda x:
          words) by
                    extract_phrases(x))
          segment.
5.
         - Slice by
                    python def get_top_keywords_by_segment(df,
Segment
         demograp
                    segment): segment_text =
Comparis
         hics: Age
                    df.groupby(segment)["Clean_Text"].apply("
on
          buckets,
                    ".join) tfidf_seg =
          Gender,
                    tfidf.fit_transform(segment_text) tfidf_seg_df =
          NCCS.
                    pd.DataFrame(tfidf_seg.toarray(),
                    index=segment_text.index,
          Compare
          TF-IDF
                    columns=tfidf.get_feature_names_out()) return
          ranks and
                    tfidf_seq_df.T.apply(lambda x:
          KeyBERT
                    x.sort_values(ascending=False).head(10)).stack()
          scores for
                    .reset_index(name="TFIDF_Score")
          uniquenes
                    keywords_by_gender =
          S.
                    get_top_keywords_by_segment(df_text, "Gender")
```

```
6. Output - Export
                    python
Tables
          keyword
                    keywords_by_gender.to_csv("segment_keywords_gend
          and
                    er.csv", index=False) df_text[['Respondent_ID',
          phrase
                    'Key_Phrases']].explode("Key_Phrases").to_csv("k
         tables for
                    ey_phrases_all.csv", index=False)
          overall
          and
          segment-
          specific
          analyses.
```

#### **Deliverables**

## **Keyword Tables**

- Overall Top Keywords (Top 20): Sorted by average TF-IDF score
- Segment Keywords (Top 10):

File: segment\_keywords\_<segment>.csv
Columns: Segment, Keyword, TFIDF\_Score, Rank

#### **Key Phrase Tables**

Overall Phrases:

Top 10 from the full dataset using KeyBERT

• Segment-Specific Phrases:

File: key\_phrases\_all.csv
Columns: Respondent\_ID, Phrase, Relevance

#### **Analysis Notebook**

- Documented Python code:
  - Preprocessing
  - o TF-IDF extraction
  - KeyBERT phrase extraction
  - Segment comparisons
- Parameters: ngram\_range=(1,2), top\_n=5, custom stopword list via spaCy

## **Summary Report**

- Highlight most unique or distinctive words and phrases by:
  - o Gender
  - o Age Bucket (<30 vs. ≥30)
  - o NCCS (A vs. B/C)
- Identify potential tags for visual dashboards and thematic filters