Analysis on Work-related Happy Moments

In [502…

```
import re
import contractions
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
from nltk.corpus import stopwords
import string
from nltk.sentiment.vader import SentimentIntensityAnalyzer
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
from nltk.corpus import wordnet
from collections import Counter
from nltk.stem import WordNetLemmatizer
from nltk.collocations import BigramAssocMeasures, BigramCollocationFinder, TrigramCol
from wordcloud import WordCloud
```

In [503…

```
def replace_words(text):
    for word, replacement in corrections.items():
        text = text.replace(word, replacement)
    return text

#Frequency functions
def entertainment_frequency(text):
    lowered_text = text.lower()
    matches = entertainment_pattern.findall(lowered_text)
    return len(matches)
def exercise_frequency(text):
    lowered_text = text.lower()
    matches = exercise_pattern.findall(lowered_text)
    return len(matches)
def family_frequency(text):
    lowered_text = text.lower()
    matches = family_pattern.findall(lowered_text)
    return len(matches)
def food_frequency(text):
    lowered_text = text.lower()
    matches = food_pattern.findall(lowered_text)
    return len(matches)
def people_frequency(text):
    lowered_text = text.lower()
    matches = people_pattern.findall(lowered_text)
    return len(matches)
def work_frequency(text):
    lowered_text = text.lower()
    matches = work_pattern.findall(lowered_text)
    return len(matches)
def school_frequency(text):
    lowered_text = text.lower()
    matches = school_pattern.findall(lowered_text)
    return len(matches)
def shopping_frequency(text):
    lowered_text = text.lower()
```

```
    matches = shopping_pattern.findall(lowered_text)
    return len(matches)
def pets_frequency(text):
    lowered_text = text.lower()
    matches = pets_pattern.findall(lowered_text)
    return len(matches)

def sentence_preprocessing(sentence):
    #Replace "`" with "'"
    sentence = sentence.replace("`","'")
    #Replace contractions
    sentence = contractions.fix(sentence)
    sentence = re.sub(r"\w+\.com",'', sentence)
    #Remove URLs
    sentence = re.sub(r"http\S+", "", sentence)
    #Remove numbers
    sentence = "".join([i for i in sentence if not i.isdigit()])
    #Remove punctuations except "$", "-", and "'"
    sentence = "".join([i for i in sentence if i not in string.punctuation or i=="$" o
    #Tokenize the sentence
    tokens = nltk.word_tokenize(sentence)
    #Remove stop words
    tokens = [token.lower() for token in tokens if token.lower() not in updated_stopwo
    return tokens
def text_correction(word):
    corrections = {
    "unde's": 'uncle',
    "uncle's": 'uncle',
    "b'day": 'birthday',
    "mother's": 'mother',
    "year's": "year",
    "bus,": "bus",
    'february,': 'february',
    "children's": 'children',
    "daughter's": 'daughter',
    "did't": "did not",
    'ndonating': 'donate',
    "god's": 'god',
    "sister's": 'sister',
    "sisters's": 'sister',
    "parent's": 'parent',
    "brother's": 'brother',
    'thrones0': 'thrones',
        "n't": 'not'
}
    if word in corrections:
        return corrections[word]
    else:
        return word

def get_part_of_speech(word):
    probable_part_of_speech = wordnet.synsets(word)
    pos_counts = Counter()
    pos_tags = ["n", "v", "a", "r", "s", "p", "i", "c", "u", "x"]
    for pos_tag in pos_tags:
        pos_counts[pos_tag] = len([item for item in probable_part_of_speech if item.po
    most_likely_part_of_speech = pos_counts.most_common(1)[0][0]
    return most_likely_part_of_speech

def rightTypes(ngram):
```

```
    for word in ngram:
        if word in stopwords.words('english') or word.isspace():
            return False
    acceptable_types = ('JJ', 'JJR', 'JJS', 'NN', 'NNS', 'NNP', 'NNPS')
    second_type = ('NN', 'NNS', 'NNP', 'NNPS')
    tags = nltk.pos_tag(ngram)
    if tags[0][1] in acceptable_types and tags[1][1] in second_type:
        return True
    else:
        return False
def bigram_noun(bigram):
    first_tag = get_part_of_speech(bigram[0])
    second_tag = get_part_of_speech(bigram[1])
    if first_tag not in ['a','n'] and second_tag != 'n':
        return False
    return True
def replace_bigram(hm_text):
    for bigram in bigrams:
        hm_text = hm_text.replace(bigram, '_'.join(bigram.split()))
    return hm_text

def noun_verb(x):
    tag = nltk.pos_tag(x)
    filtered_tokens = [word[0] for word in tag if word[1].startswith("N")]
    return filtered_tokens

def topic_counts(df):
    topic_counts_list = dict()
    for topic in topic_list:
        topic_counts_list[topic] = (df[topic]!=0).sum()
    topic_counts = dict(sorted(topic_counts_list.items(), key=lambda x: x[1], reverse=
    return topic_counts
```

In [504…

```
hm = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\cleaned_hm.csv", encoding = "utf-8")
demographic = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\demographic.csv", encoding
vad = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\vad.csv", encoding="utf-8")
sense_label = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\senselabel.csv", encoding='

#Create a topic dictionary
entertainment = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\entertainment-dict.csv",
exercise = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\exercise-dict.csv", encoding='
family = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\family-dict.csv", encoding="utf-
food = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\food-dict.csv", encoding="utf-8",
people = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\people-dict.csv", encoding="utf-
school = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\school-dict.csv", encoding="utf-
work = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\work-dict.csv", encoding="utf-8",
shopping = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\shopping-dict.csv", encoding='
pets = pd.read_csv(r"C:\Users\wangj\Desktop\HappyDB\pets-dict.csv", encoding="utf-8",

topic_dictionary = dict()
topic_dictionary["entertainment"] = entertainment[0].tolist()
topic_dictionary["exercise"] = exercise[0].tolist()
topic_dictionary["family"] = family[0].tolist()
topic_dictionary["food"] = food[0].tolist()
topic_dictionary["people"] = people[0].tolist()
topic_dictionary["school"] = school[0].tolist()
topic_dictionary["work"] = work[0].tolist()
topic_dictionary["shopping"] = shopping[0].tolist()
topic_dictionary["pets"] = pets[0].tolist()
```

In [505…
```
hm[["hmid","wid"]] = hm[["hmid","wid"]].astype(str)
vad["hmid"] = vad["hmid"].astype(str)
demographic["wid"] = demographic["wid"].astype(str)
sense_label["hmid"] = sense_label["hmid"].astype(str)
```

Data Preprocessing

In [506…
```
custom_stopwords = []
updated_stopwords = set(stopwords.words("english")).union(custom_stopwords)
```

In [507…
```
lemma_df = pd.DataFrame()
lemma_df["hmid"] = hm["hmid"]
lemma_df["wid"] = hm["wid"]
lemma_df["reflection_period"] = hm["reflection_period"]
lemma_df["cleaned_hm"] = hm["cleaned_hm"]
lemma_df["original_tokens"] = lemma_df["cleaned_hm"].apply(sentence_preprocessing)
lemma_df = lemma_df.explode('original_tokens', ignore_index=True)
```

In [508…
```
lemma_df = lemma_df.dropna()
lemma_df["original_tokens"] = lemma_df["original_tokens"].replace("$","money")
lemma_df["tokens"] = lemma_df["original_tokens"].apply(lambda x: re.sub(r"^[-']+$",'',
lemma_df["tokens"] = lemma_df["tokens"].apply(lambda x: re.sub(r"^\W*|\W*$",'', x))
lemma_df = lemma_df[(lemma_df["tokens"]!='')&(~lemma_df["tokens"].str.startswith("'")
lemma_df = lemma_df[(lemma_df["tokens"]!='')&(~lemma_df['tokens'].isin(list(string.pur
lemma_df["tokens"] = lemma_df["tokens"].apply(text_correction)
lemma_df = lemma_df[lemma_df['tokens'].str.len() != 2]
lemma_df
```

Out[508]:

	hmid	wid	reflection_period	cleaned_hm	original_tokens	tokens
0	27673	2053	24h	I went on a successful date with someone I fel...	went	went
1	27673	2053	24h	I went on a successful date with someone I fel...	successful	successful
2	27673	2053	24h	I went on a successful date with someone I fel...	date	date
3	27673	2053	24h	I went on a successful date with someone I fel...	someone	someone
4	27673	2053	24h	I went on a successful date with someone I fel...	felt	felt
...	...	...	...	...	...	...
903989	128765	1629	24h	I had a great meeting yesterday at work with m...	team	team
903990	128766	141	24h	I had a great workout last night.	great	great
903991	128766	141	24h	I had a great workout last night.	workout	workout
903992	128766	141	24h	I had a great workout last night.	last	last
903993	128766	141	24h	I had a great workout last night.	night	night

889179 rows × 6 columns

In [509…

```
lemmatizer = WordNetLemmatizer()
lemma_df["tokens"] = lemma_df["tokens"].apply(lambda x: lemmatizer.lemmatize(x, get_pa
lemma_df = lemma_df[~lemma_df['tokens'].isin(list(updated_stopwords))]
```

In [510…

```
#Delete duplicated rows
lemma_df = lemma_df.groupby(["hmid","wid","reflection_period","cleaned_hm"]).agg(list)
lemma_df["tokens"] = lemma_df["tokens"].apply(tuple)
lemma_df = lemma_df.drop_duplicates(subset="tokens")
lemma_df["tokens"] = lemma_df["tokens"].apply(list)
lemma_df
```

Out[510]:

	hmid	wid	reflection_period	cleaned_hm	tokens
0	100000	884	3m	I bought cute earrings	[buy, cute, earring]
1	100001	560	3m	Last month my children took a tour.	[last, month, child, take, tour]
2	100002	395	3m	I finished reading the New Testament fully. I ...	[finish, read, new, testament, fully, super, h...
3	100003	10079	3m	Was awarded employee of the month at work, mad...	[award, employee, month, work, make, feel, app...
4	100004	2905	3m	I made plans to meet up with a girl I like.	[make, plan, meet, girl, like]
...	...	...	...	...	...
100529	99994	334	3m	I went out to eat with my girlfriend and we ta...	[go, eat, girlfriend, talk, game, play]
100531	99996	2294	3m	I was happy when I was able to lose several po...	[happy, able, lose, several, pound, week, diet]
100532	99997	8044	3m	Helped the elderly neighbor lady get her coole...	[help, elderly, neighbor, lady, get, cooler, w...
100533	99998	2473	3m	My macaroni and cheese turned out perfect and ...	[macaroni, cheese, turn, perfect, best, macaro...
100534	99999	245	3m	Dr. Pepper. Seriously. I've always got one i...	[pepper, seriously, always, get, one, hand, en...

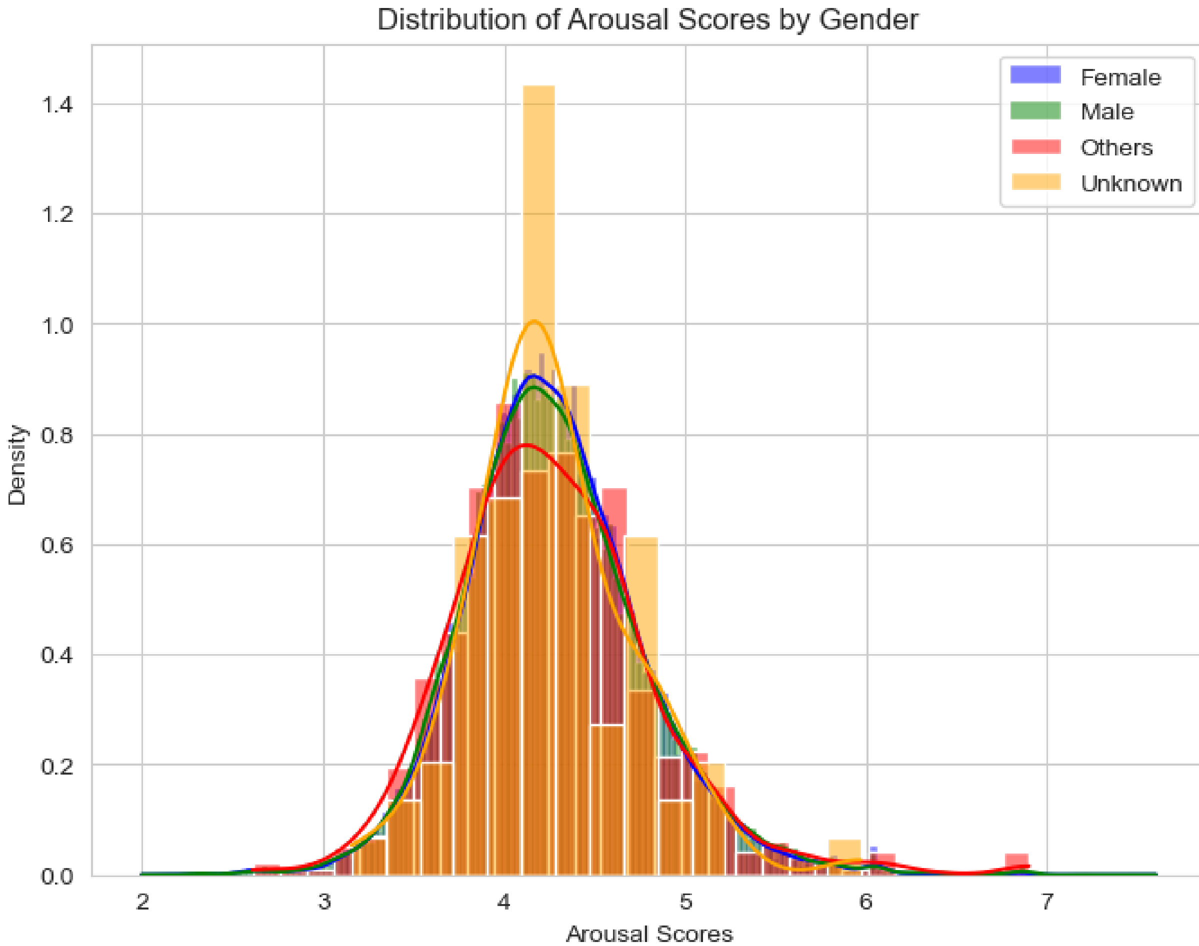
92613 rows × 5 columns

Sentimental Analysis

Sentimental intensity based on gender

In [618…

```
#Gender
demographic_vad = pd.merge(lemma_demographic, vad, on="hmid", how= "inner")
plt.figure(figsize=(8, 6))
sns.histplot(demographic_vad[demographic_vad["gender"]=="f"]["arousal"], kde=True, co
sns.histplot(demographic_vad[demographic_vad["gender"]=="m"]["arousal"], kde=True, co
sns.histplot(demographic_vad[demographic_vad["gender"]=="o"]["arousal"], kde=True, co
sns.histplot(demographic_vad[demographic_vad["gender"].isna()]["arousal"], kde=True, c
plt.xlabel("Arousal Scores")
plt.ylabel("Density")
plt.title("Distribution of Arousal Scores by Gender")
plt.legend()
plt.show()
```



We consider the arousal score as an approximation of sentiment intensity. On average, individuals with an unknown gender tend to have the highest arousal scores. Females and males exhibit very similar arousal scores, while individuals in other gender categories tend to have lower arousal scores on average.

LDA Modeling

In [511…

```
#PMI
bigram_finder = BigramCollocationFinder.from_documents(lemma_df["tokens"].tolist())
bigram_finder.apply_freq_filter(300)
pmi_scores = bigram_finder.score_ngrams(BigramAssocMeasures.pmi)
bigram_pmi= pd.DataFrame(pmi_scores)
bigram_pmi.columns = ['bigram','pmi']
bigram_pmi.sort_values(by="pmi")
print(bigram_pmi)

#Raw Frequency
bigram_freq = bigram_finder.ngram_fd.items()
bigramFreqTable = pd.DataFrame(list(bigram_freq), columns=['bigram','freq']).sort_valu
filtered_bi = bigramFreqTable[bigramFreqTable.bigram.map(lambda x: rightTypes(x))]
filtered_bi.head(20)
```

	bigram	pmi
0	(ice, cream)	10.229734
1	(even, though)	9.178284
2	(video, game)	7.319223
3	(family, member)	7.172168
4	(birthday, party)	6.741822
5	(last, night)	6.269185
6	(week, ago)	6.009067
7	(three, month)	5.850477
8	(month, ago)	5.689437
9	(friend, mine)	5.600532
10	(year, old)	5.594157
11	(past, month)	5.579887
12	(watch, movie)	5.478580
13	(best, friend)	5.429124
14	(moment, life)	5.409451
15	(first, time)	5.243584
16	(come, home)	5.185817
17	(long, time)	5.121555
18	(come, visit)	5.111170
19	(last, week)	5.084441
20	(spend, time)	5.072777
21	(two, week)	4.925604
22	(last, month)	4.921924
23	(come, back)	4.865325
24	(event, make)	4.790289
25	(one, favorite)	4.781163
26	(buy, new)	4.743314
27	(mother, day)	4.557713
28	(really, enjoy)	4.322585
29	(new, car)	4.298445
30	(happy, moment)	4.297906
31	(make, happy)	4.199411
32	(old, friend)	4.163076
33	(really, good)	4.142044
34	(new, job)	4.028709
35	(make, feel)	3.981680
36	(day, ago)	3.976826
37	(felt, happy)	3.955750
38	(feel, good)	3.721376
39	(happy, past)	3.510639
40	(feel, happy)	3.415862
41	(great, time)	3.250324
42	(home, work)	3.195281
43	(finally, get)	3.133879
44	(really, happy)	2.532003
45	(friend, see)	2.504243
46	(get, new)	2.473303
47	(happy, see)	2.408844
48	(get, spend)	2.354813
49	(get, home)	2.280053
50	(able, get)	2.189814
51	(get, see)	2.132532
52	(day, work)	2.011491
53	(good, friend)	1.982026
54	(make, really)	1.953674
55	(get, good)	1.859973
56	(get, work)	0.663875
57	(happy, get)	0.606148

Out[511]:

	bigram	freq
43	(last, night)	1966
6	(first, time)	1728
31	(long, time)	1254
32	(happy, moment)	1178
29	(event, make)	1162
0	(last, month)	1161
15	(last, week)	1074
21	(spend, time)	961
48	(best, friend)	850
35	(video, game)	679
38	(old, friend)	670
13	(happy, see)	651
33	(happy, get)	645
47	(past, month)	539
40	(able, get)	526
51	(ice, cream)	497
3	(new, job)	484
46	(happy, past)	469
25	(family, member)	428
52	(home, work)	412

In [512…

```
filtered_bigram = bigram_pmi[(bigram_pmi['bigram'].apply(lambda x: bigram_noun(x)))&(b
filtered_bigram
bigrams = [' '.join(x) for x in filtered_bigram['bigram'].values]
lemma_df = pd.DataFrame()
lemma_df["hmid"] = hm["hmid"]
lemma_df["wid"] = hm["wid"]
lemma_df["original_tokens"] = hm["cleaned_hm"].apply(replace_bigram)
lemma_df["original_tokens"] = lemma_df["original_tokens"].apply(sentence_preprocessing
lemma_df = lemma_df.explode('original_tokens', ignore_index=True)
lemma_df = lemma_df.dropna()
lemma_df["original_tokens"] = lemma_df["original_tokens"].replace("$","money")
lemma_df["tokens"] = lemma_df["original_tokens"].apply(lambda x: re.sub(r"^[-']+$",'',
lemma_df["tokens"] = lemma_df["tokens"].apply(lambda x: re.sub(r"^\W*|\W*$",'', x))
lemma_df = lemma_df[(lemma_df["tokens"]!='')&(~lemma_df["tokens"].str.startswith("'"))
lemma_df = lemma_df[(lemma_df["tokens"]!='')&(~lemma_df['tokens'].isin(list(string.pun
lemma_df["tokens"] = lemma_df["tokens"].apply(text_correction)
lemma_df = lemma_df[lemma_df['tokens'].str.len() != 2]
lemma_df["tokens"] = lemma_df["tokens"].apply(lambda x: lemmatizer.lemmatize(x, get_pa
lemma_df = lemma_df[~lemma_df['tokens'].isin(list(updated_stopwords))]
lemma_df = lemma_df.groupby(["hmid","wid"]).agg(list)["tokens"].reset_index()
lemma_df["tokens"] = lemma_df["tokens"].apply(tuple)
lemma_df = lemma_df.drop_duplicates(subset="tokens")
```

```
lemma_df["tokens"] = lemma_df["tokens"].apply(list)
lemma_copy = lemma_df.copy()
lemma_copy["tokens"] = lemma_copy["tokens"].apply(lambda x: noun_verb(x))
lemma_demographic = pd.merge(lemma_copy, demographic, on = "wid", how = "left")
```

In [526…

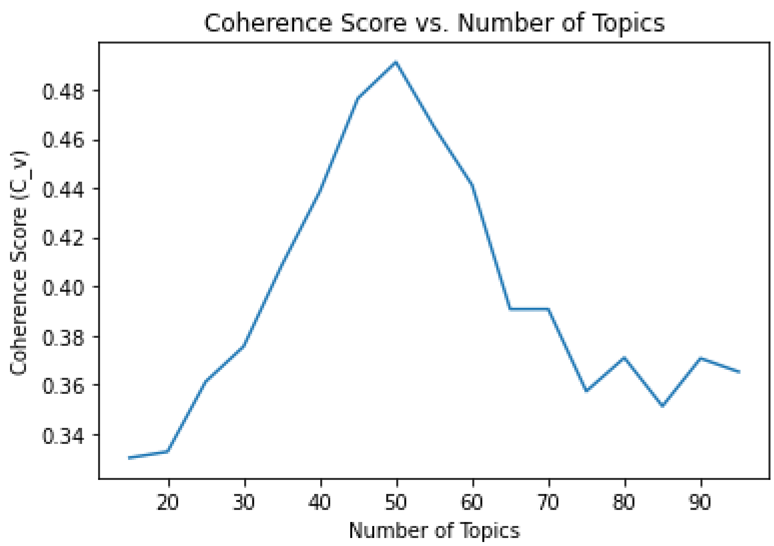
```
from gensim import corpora, models
from gensim.models import LdaModel, CoherenceModel
documents = lemma_demographic["tokens"].tolist()
dictionary = corpora.Dictionary(documents)
corpus = [dictionary.doc2bow(doc) for doc in documents]
lda_model = models.LdaModel(corpus, num_topics=37, id2word=dictionary, random_state=42
for topic_id, topic_terms in lda_model.show_topics(num_words=10,num_topics=-1, formatt
    print(f"Topic {topic_id}: {', '.join([term[0] for term in topic_terms])}")
print("Perplexity Score:", lda_model.log_perplexity(corpus))
coherence_model = CoherenceModel(model=lda_model, texts=documents, dictionary=dictiona
coherence_score = coherence_model.get_coherence()
print("Coherence Score:", coherence_score)
```

```
Topic 0: life, moment, amount, study, month, rest, cost, time, tournament, teacher
Topic 1: play, order, game, mail, video_game, ask, online, eye, brand, repair
Topic 2: night, shop, date, catch, change, raise, bit, debt, loan, payment
Topic 3: friend, birthday, celebrate, move, party, time, everyone, travel, church, sm
ile
Topic 4: pay, pass, person, bill, test, group, exam, everything, grade, water
Topic 5: gift, surprise, manage, amaze, bike, birthday, festival, come, player, caree
r
Topic 6: yesterday, weekend, make, thing, concert, face, fall, stock, time, trump
Topic 7: event, watch, girlfriend, card, month, pizza, breakfast, credit, paper, hote
l
Topic 8: help, city, pound, egg, amazon, effort, guitar, steak, view, appreciate
Topic 9: husband, vacation, first_time, end, computer, song, find, minute, excite, re
lease
Topic 10: trip, mom, place, enjoy, plan, lot, apartment, run, clothe, treat
Topic 11: movie, food, ticket, boyfriend, meal, watch, eat, childhood, income, gas
Topic 12: baby, lunch, someone, use, buy, part, item, rain, plant, care
Topic 13: week, month, doctor, country, drink, last_night, golf, letter, word, reach
Topic 14: book, talk, phone, beach, bar, ice_cream, new_car, relationship, stop, tele
vision
Topic 15: year, visit, try, best_friend, wait, mturk, return, month, uncle, join
Topic 16: school, child, program, hug, graduate, story, board, function, write, art
Topic 17: walk, way, long_time, couple, sit, weather, room, problem, turn, felt
Topic 18: purchase, happiness, experience, world, check, feel, two_weeks, task, pool,
flight
Topic 19: home, dad, work, joy, idea, bathroom, discover, mood, situation, month
Topic 20: show, fun, parent, watch, sale, favorite, spring, lot, pair, series
Topic 21: tell, company, music, marriage, wedding, interest, band, today, manager, gy
m
Topic 22: kid, girl, cousin, dance, galaxy, attend, cake, march, sign, piece
Topic 23: saw, call, cook, office, picture, heart, birthday_party, dress, theater, ya
rd
Topic 24: work, money, brother, project, something, bos, today, bonus, time, lot
Topic 25: game, meet, team, store, love, goal, season, baseball, share, grocery
Topic 26: wife, house, look, cat, break, time, wake, take, spend, law
Topic 27: day, mother, time, drive, news, name, father, feel, today, quality
Topic 28: get, road, woman, proud, performance, laugh, challenge, contact, hear, lot
Topic 29: dog, town, dollar, mine, business, hang, ride, compliment, memory, pet
Topic 30: job, sister, summer, promotion, interview, semester, offer, partner, receiv
e, shoe
Topic 31: hour, people, last_month, health, thank, hospital, post, worry, bank, eveni
ng
Topic 32: dinner, park, think, beer, tonight, photo, sun, nice, colleague, club
Topic 33: daughter, eat, college, class, restaurant, student, conversation, need, gra
duation, hand
Topic 34: son, garden, learn, neighbor, fix, relax, birth, sleep, university, stay
Topic 35: start, see, morning, coffee, last_week, result, course, match, hit, opportu
nity
Topic 36: family, car, state, bring, three_months, deal, time, price, exercise, score
Perplexity Score: -13.081510775272035
Coherence Score: 0.3969620276336725
```

In [112…

```python
from gensim.models import LdaModel
from gensim.corpora import Dictionary
from gensim.models.coherencemodel import CoherenceModel
import matplotlib.pyplot as plt

topic_range = range(15, 100, 5)
coherence_scores = []
for num_topics in topic_range:
```

```
    lda_model = LdaModel(corpus, num_topics=num_topics, id2word=dictionary, random_sta
    coherence_model = CoherenceModel(model=lda_model, texts=documents, dictionary=dict
    coherence_score = coherence_model.get_coherence()
    coherence_scores.append(coherence_score)

plt.plot(topic_range, coherence_scores)
plt.xlabel("Number of Topics")
plt.ylabel("Coherence Score (C_v)")
plt.title("Coherence Score vs. Number of Topics")
plt.show()
```



Although coherence score reaches peak at 50 number of topics, when we examine those topics, they are not very interpretable. Thus we chose 37 number of topics.

In [527…

```
topic_assignments = []
for doc in documents:
    bow = dictionary.doc2bow(doc)
    topic_distribution = lda_model.get_document_topics(bow)
    topic_assignment = max(topic_distribution, key=lambda x: x[1])
    topic_assignments.append(topic_assignment[0])
lemma_demographic["topics"] = topic_assignments
```

In [529…

```
topic_labels = {
    0: "others",
    1: "others",
    2: "others",
    3: "celebration",
    4: "others",
    5: "gifting",
    6: "others",
    7: "others",
    8: "others",
    9: "others",
    10: "others",
    11: "entertainment and food",
    12: "others",
    13: "others",
    14: "others",
    15: "others",
    16: "school",
    17: "others",
```

```
    18: "shopping",
    19: "others",
    20: "others",
    21: "others",
    22: "others",
    23: "others",
    24: "work",
    25: "entertainment and shopping",
    26: "others",
    27: "others",
    28: "others",
    29: "others",
    30: "work",
    31: "health",
    32: "leisure",
    33: "school and food",
    34: "others",
    35: "others",
    36: "others"
}
lemma_demographic["topics"] = lemma_demographic["topics"].map(topic_labels)
```

Out[529]:

	hmid	wid	tokens	age	country	gender	marital	parenthood	topics
0	100000	884	[earring]	22.0	USA	f	married	n	others
1	100001	560	[month, tour]	33	IND	m	married	y	others
2	100002	395	[jesus, mission, life, way]	33.0	USA	m	single	n	others
3	100003	10079	[employee, month, work, feel, appreciate]	22	USA	m	single	y	others
4	100004	2905	[plan, girl]	20.0	USA	m	single	n	others
...	...	...	...	...	...	...	...	...	...
92647	99994	334	[girlfriend, talk, game, play]	23	USA	f	single	n	others
92648	99996	2294	[pound, week]	28	USA	f	single	n	others
92649	99997	8044	[help, neighbor, work, summer, thank, get]	43	UGA	m	divorced	y	others
92650	99998	2473	[macaroni, turn, macaroni, cheese]	41	USA	m	divorced	n	others
92651	99999	245	[pepper, hand, enjoy, day, husband, blood, pep...	33.0	USA	f	married	y	others

92652 rows × 9 columns

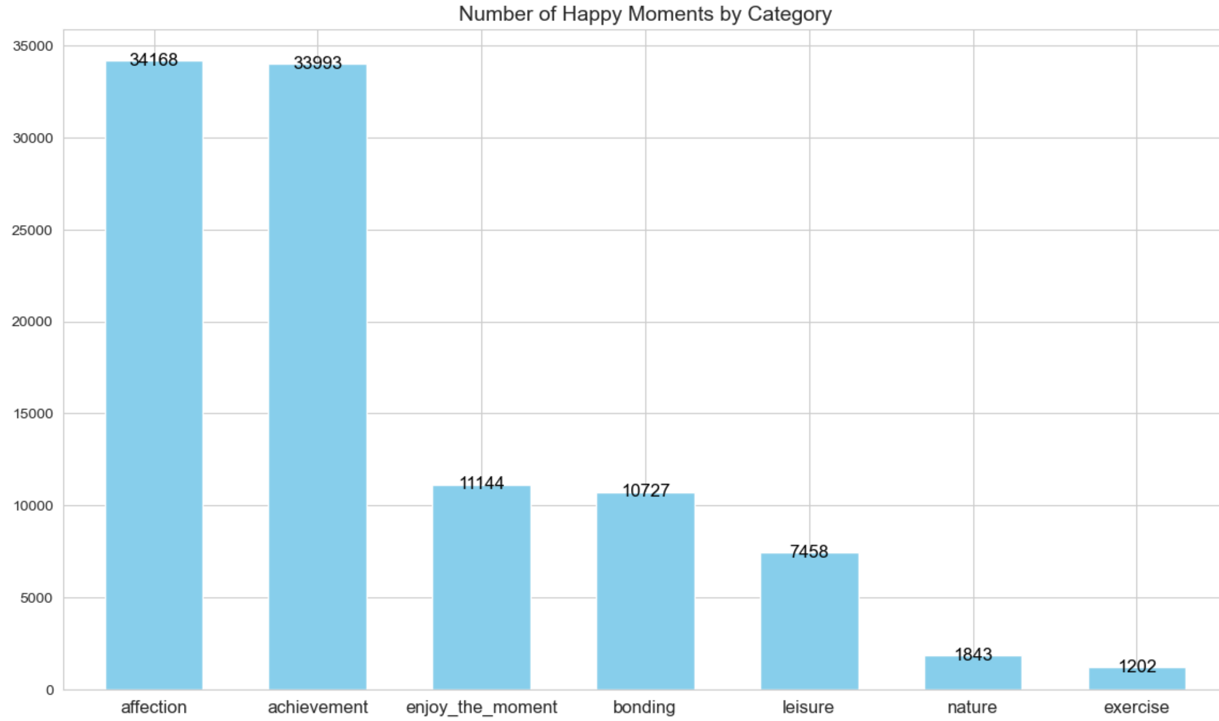
In [530…

```
#Assigning topic lables to each happy moment
corrections = {
    'unde`s': 'uncle',
    'uncle`s': 'uncle',
    "b'day": 'birthday',
    'mother`s': 'mother',
    "ma'am": 'mother',
```

```
    'can`t': "can't",
    'cant': "can't",
    "year's": "year",
    "bus,": "bus",
    'february,': 'february',
    'children`s': 'children',
    'daughter`s': 'daughter',
    "did't": "did not",
    "didnt": "did not",
    'n\\donating': 'donate',
    'god`s': 'god',
    "april'": 'april',
    'sister`s': 'sister',
    'sisters`s': 'sister',
    'parent`s': 'parent',
    'brother`s': 'brother',
    'thrones0': 'thrones',
    'wont': "won't",
    "n't": 'not'
}

hm["cleaned_hm"] = hm["cleaned_hm"].apply(replace_words)
entertainment_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, entertainment[0]))
exercise_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, exercise[0])) + r')\b',
family_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, family[0])) + r')\b', re.
food_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, food[0])) + r')\b', re.IGNO
people_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, people[0])) + r')\b', re.
school_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, school[0])) + r')\b', re.
work_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, work[0])) + r')\b', re.IGNO
shopping_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, shopping[0])) + r')\b',
pets_pattern = re.compile(r'\b(' + '|'.join(map(re.escape, pets[0])) + r')\b', re.IGNO

hm["entertainment"] = hm["cleaned_hm"].apply(entertainment_frequency)
hm["exercise"] = hm["cleaned_hm"].apply(exercise_frequency)
hm["family"] = hm["cleaned_hm"].apply(family_frequency)
hm["food"] = hm["cleaned_hm"].apply(food_frequency)
hm["people"] = hm["cleaned_hm"].apply(people_frequency)
hm["school"] = hm["cleaned_hm"].apply(school_frequency)
hm["work"] = hm["cleaned_hm"].apply(work_frequency)
hm["shopping"] = hm["cleaned_hm"].apply(shopping_frequency)
hm["pets"] = hm["cleaned_hm"].apply(pets_frequency)
```

In [531…

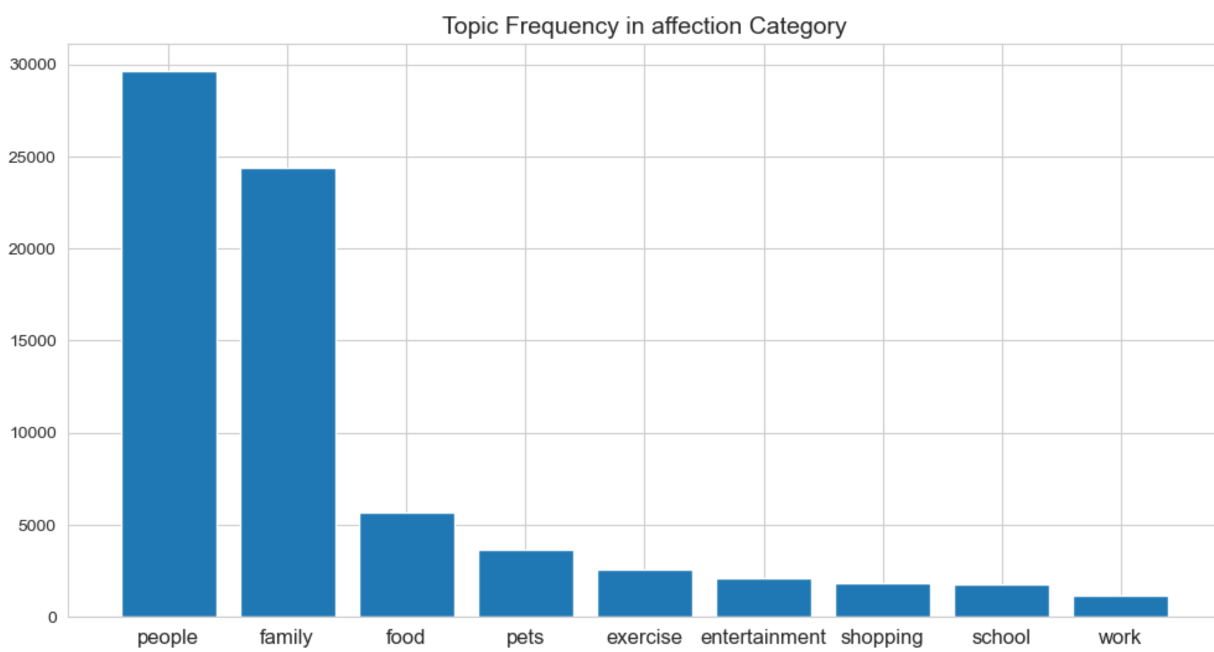
```
plt.figure(figsize=(14, 8))
ax = hm["predicted_category"].value_counts().plot(kind='bar', color='skyblue', width =
for p in ax.patches:
    ax.annotate(f'{p.get_height():.0f}', (p.get_x() + p.get_width() / 2., p.get_height
                ha='center', va='center', fontsize=12, color='black')
plt.title('Number of Happy Moments by Category', fontsize=14)
plt.xticks(rotation=360, fontsize=12)
plt.show()
```

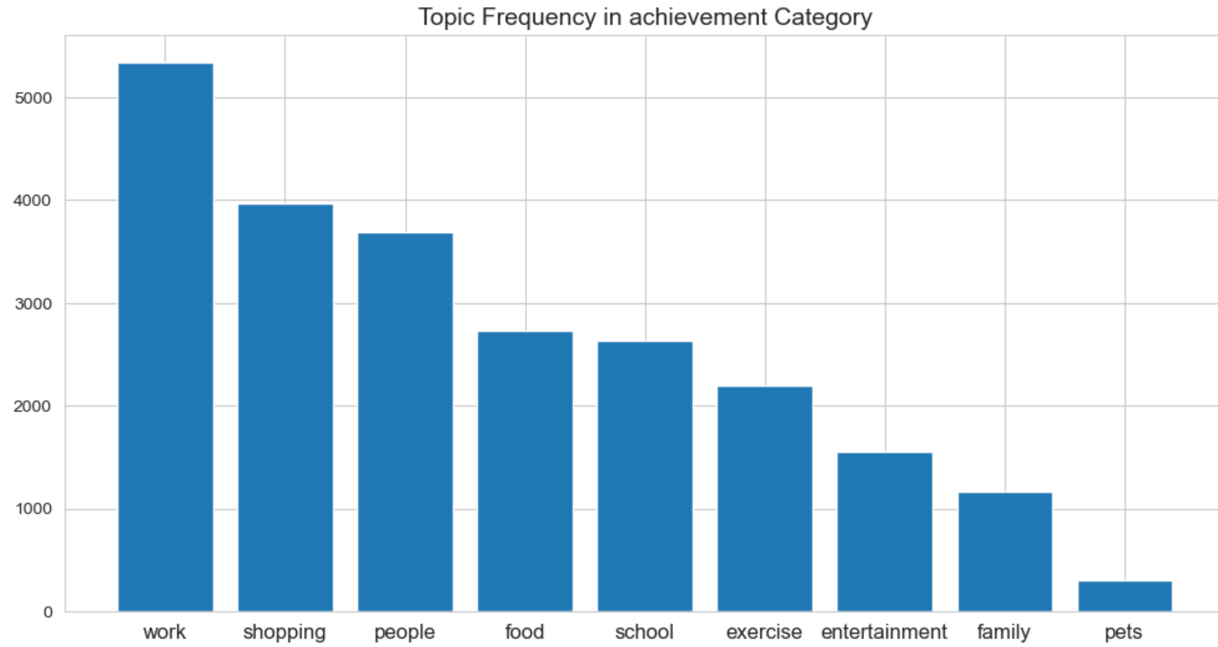


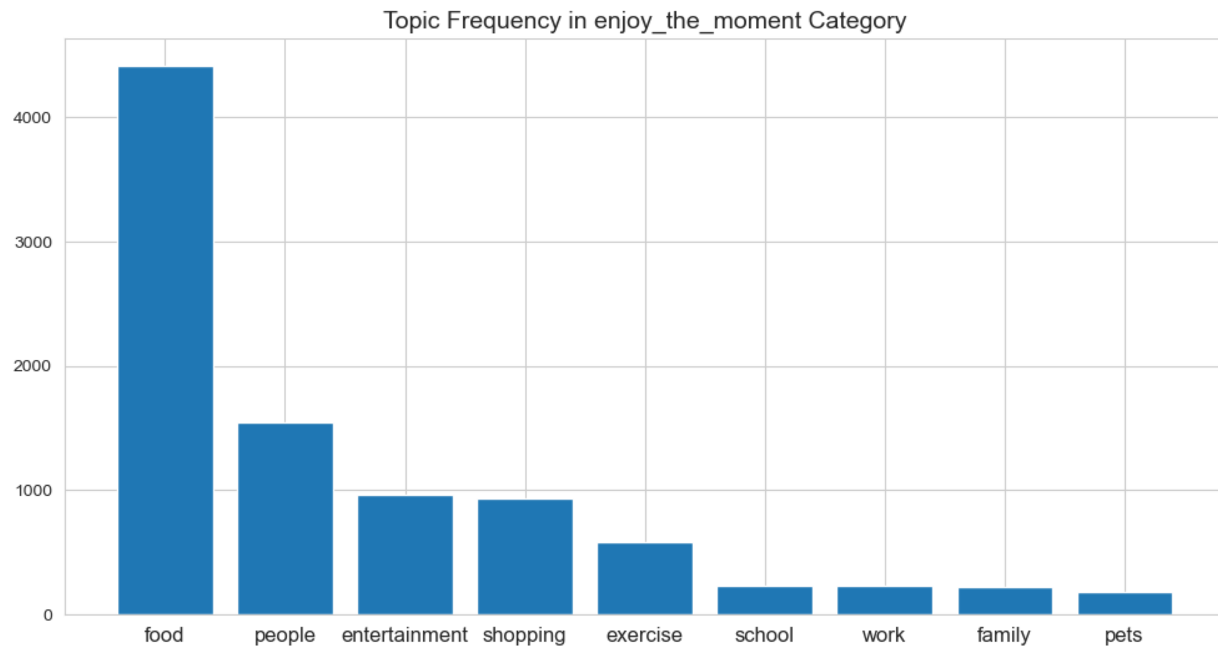
We have 7 predicted happiness categories for happy moments (affection, achievement, enjoy_the_moment, bonding, leisure, nature, exercise). Since these categories are very general, we want to know for each category, what are the most prevalent topics using our manually created topic dictionary.

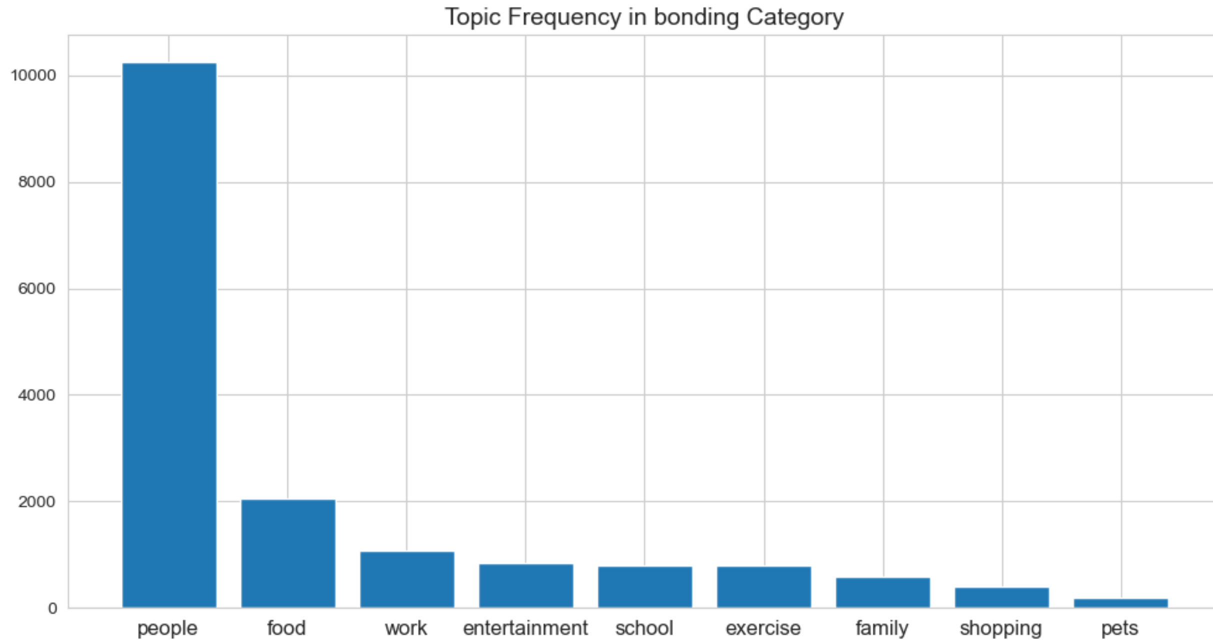
In [532…

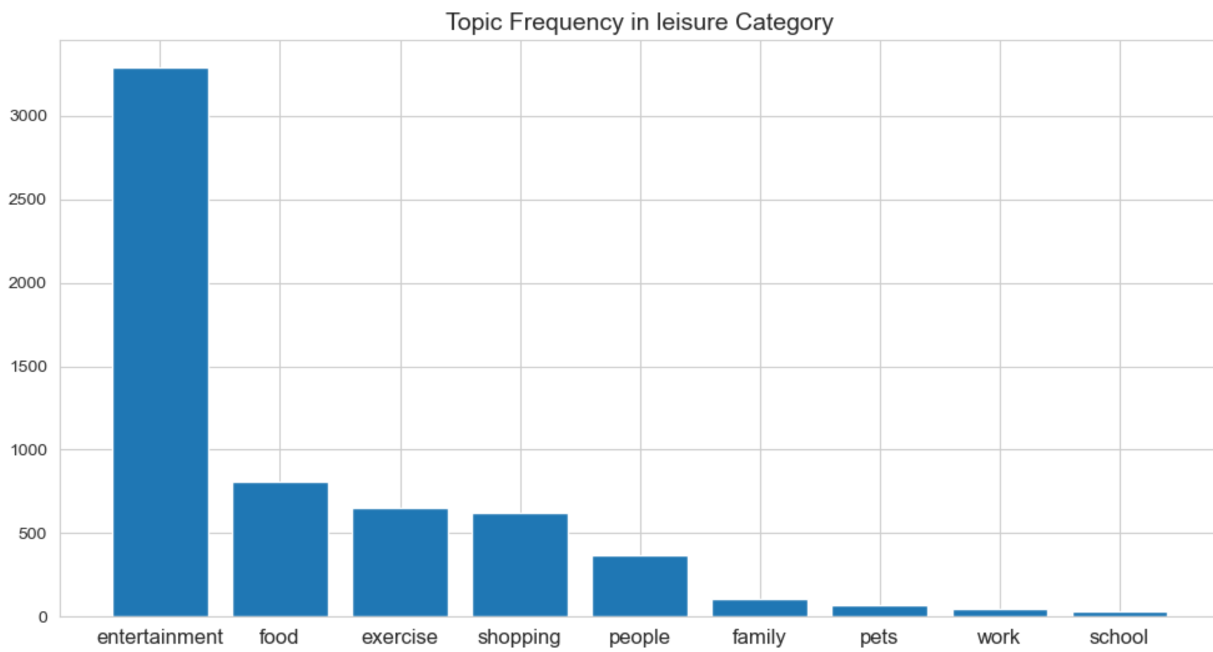
```
topic_list = ["entertainment","exercise","family","food","people","school","work","sho
happiness_category = ["affection", "achievement", "enjoy_the_moment", "bonding", "leis
for category in happiness_category:
    df = hm[hm["predicted_category"]==category]
    plt.figure(figsize=(12, 6))
    plt.bar(list(topic_counts(df).keys()),list(topic_counts(df).values()) )
    plt.title(f'Topic Frequency in {category} Category', fontsize=14)
    plt.xticks(fontsize=12)
```

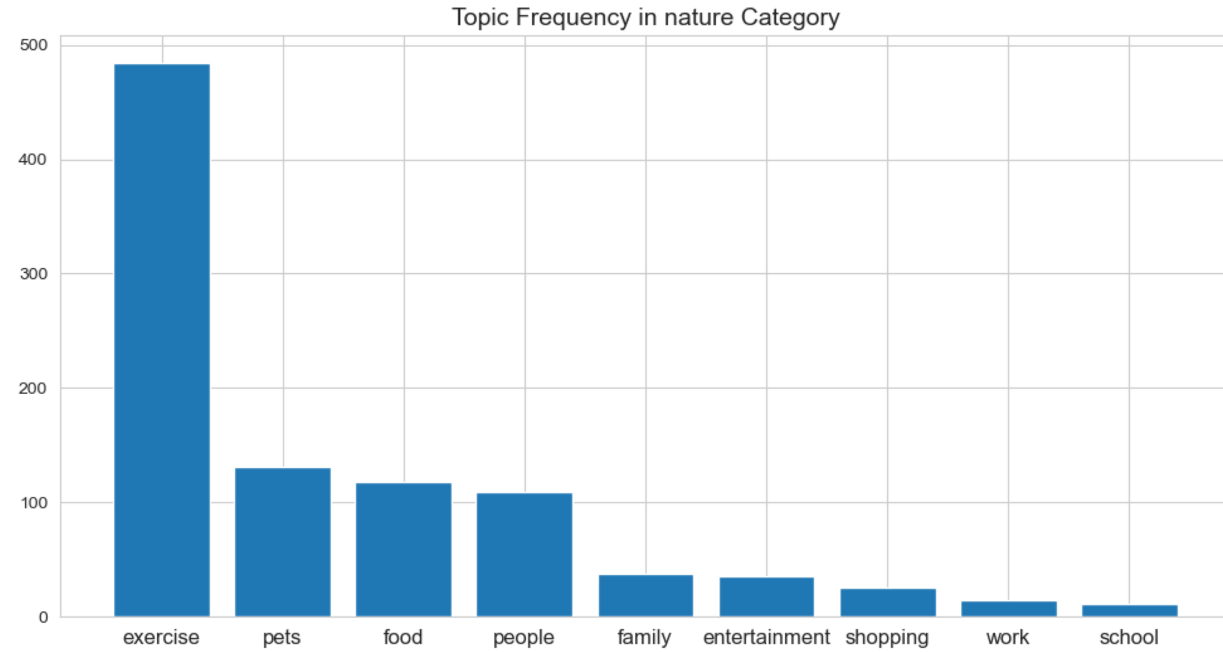


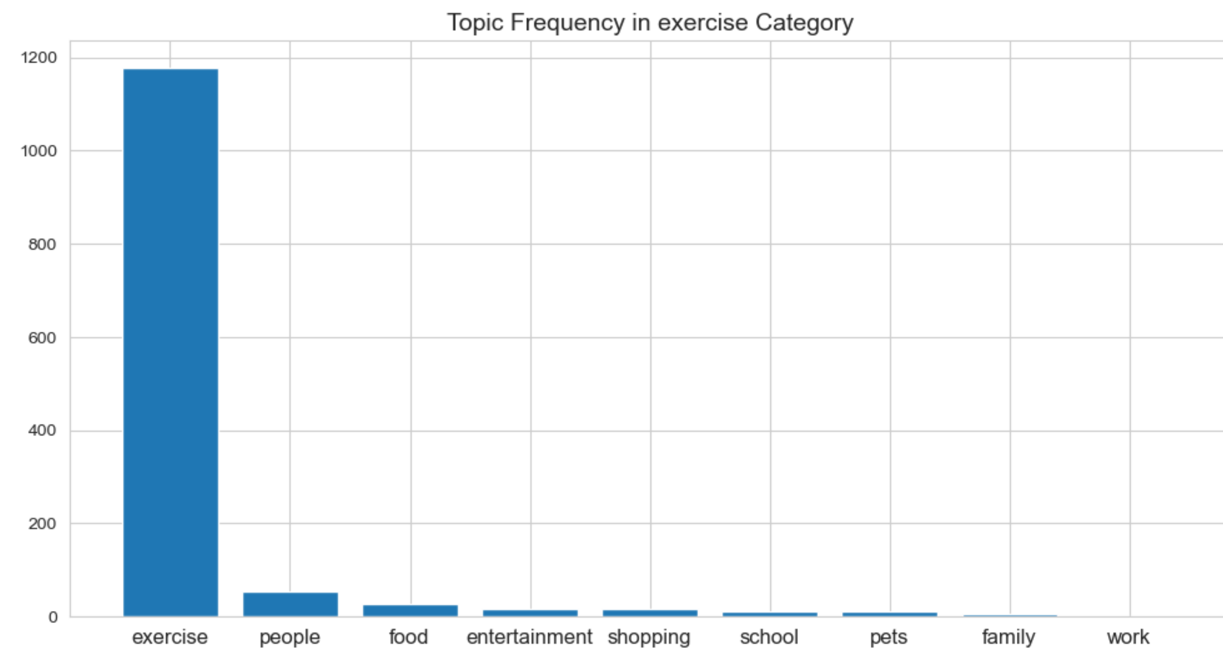

Topic Frequency in achievement Category
5000
4000
3000
2000
1000
0
work
shopping
people
food
school
exercise
entertainment
family
pets


Topic Frequency in enjoy_the_moment Category
4000
3000
2000
1000
0
food
people
entertainment
shopping
exercise
school
work
family
pets


Topic Frequency in bonding Category
10000
8000
6000
4000
2000
0
people
food
work
entertainment
school
exercise
family
shopping
pets


Topic Frequency in leisure Category
3000
2500
2000
1500
1000
500
0
entertainment
food
exercise
shopping
people
family
pets
work
school





In the affection category, happy moments are mostly about people and family. In the achievement category, happy moments are mostly about work, shopping, and people. In the enjoy_the_moment category, happy moments are mostly about food. In the bonding category, happy moments are mostly about people. In the leisure category, it's mostly about entertainment. In the nature category, happy moments are mostly about exercise. While in the exercise category, it's obvious that it's mostly about exercise.

Analysis on work-related topic

Work appears to be the most prominent and frequent topic in this happy moments database. However, it's important to clarify that when we refer to "work," we are specifically addressing work-related topics within the context of office environments. The term "work" might seem unusual in the context of happiness, as it can sometimes encompass various situations. For example, some happy moments labeled as "work" in the topic dictionary may not necessarily revolve around office work (e.g., "Last month, I received a raise in my salary and treated my family to a restaurant outing. We were very happy spending quality time together, enjoying our favorite dishes, and doing some shopping.") This is where LDA comes into play. LDA results help us ensure that the sentence's central theme is work-related. Additionally, the topic dictionary assists in refining LDA results by filtering out noise. Consequently, we combine LDA results and the topic dictionary to gain insights into why work brings happiness to people.

In [536…

```
token_topic = pd.merge(lemma_demographic[["hmid","tokens","age","country","gender","ma
topic_list = ["entertainment","exercise","family","food","people","school","shopping",
max_topic = token_topic.loc[:, topic_list].idxmax(axis=1)
condition1 = (token_topic["work"] >= token_topic.lookup(token_topic.index, max_topic))
condition2 = (token_topic.loc[:, topic_list] == 0).all(axis=1)&(token_topic["work"] !=
work_topic = token_topic[(condition1)|(condition2)]
```

Out[536]:

	hmid	tokens	age	country	gender	marital	parenthood	topics	wid	reflection_pe
3	100003	[employee, month, work, feel, appreciate]	22	USA	m	single	y	others	10079	
26	100026	[work]	37	USA	m	married	y	work	95	
67	100067	[promotion, job]	22	USA	m	single	n	work	11329	
92	100092	[bonus, payday, reward, work, feel, appreciate]	26	SRB	m	single	n	work	41	
93	100093	[new_car, promotion, encourage, selfi, giftit,...	29.0	IND	f	married	y	work	1367	
...	...	...	...	...	...	...	...	...	...	
92468	99784	[bos, work, today]	34	USA	f	single	n	work	590	
92533	99861	[promotion, job, surprise]	26.0	USA	m	single	n	work	5084	
92590	99924	[bos, bonus, year]	51	USA	m	divorced	y	work	6524	
92596	99931	[job, train]	36	IND	m	married	y	work	377	
92642	99988	[pay, job, make]	28	USA	m	married	y	work	1617	

4524 rows × 25 columns

What brings people happy at work?

In [556…

```
work_tokens = []
for token_list in work_topic["tokens"]:
    work_tokens += token_list
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(" ".jo
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('WordCloud of Work-Related Happy Moments', fontsize = 20, y = 1.1)
plt.show()
```

Factors contributing to workplace happiness include co-workers, company, boss, office, promotions, and money. Creating a comfortable and supportive workspace is crucial, as it often has a more significant impact on people's happiness than financial compensation. And it's a well-known fact that happy employees tend to be more productive.

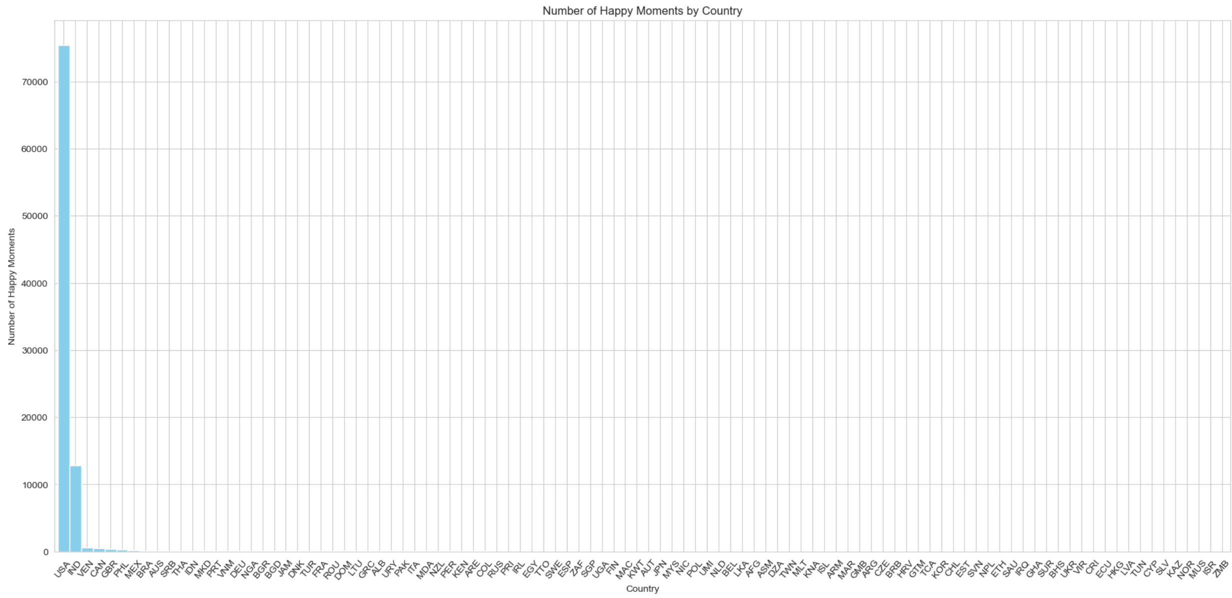
Which countries prioritize work as their source of happy moments?

In [613…

```
#Number of Happy moments by Country
plt.figure(figsize=(22, 10))
lemma_demographic["country"].value_counts().plot(kind='bar', color='skyblue', width =
plt.title('Number of Happy Moments by Country')
plt.xticks(rotation=50)
plt.xlabel('Country')
plt.ylabel('Number of Happy Moments')
plt.show()
```

Out[613]:

```
Text(0, 0.5, 'Number of Happy Moments')
```

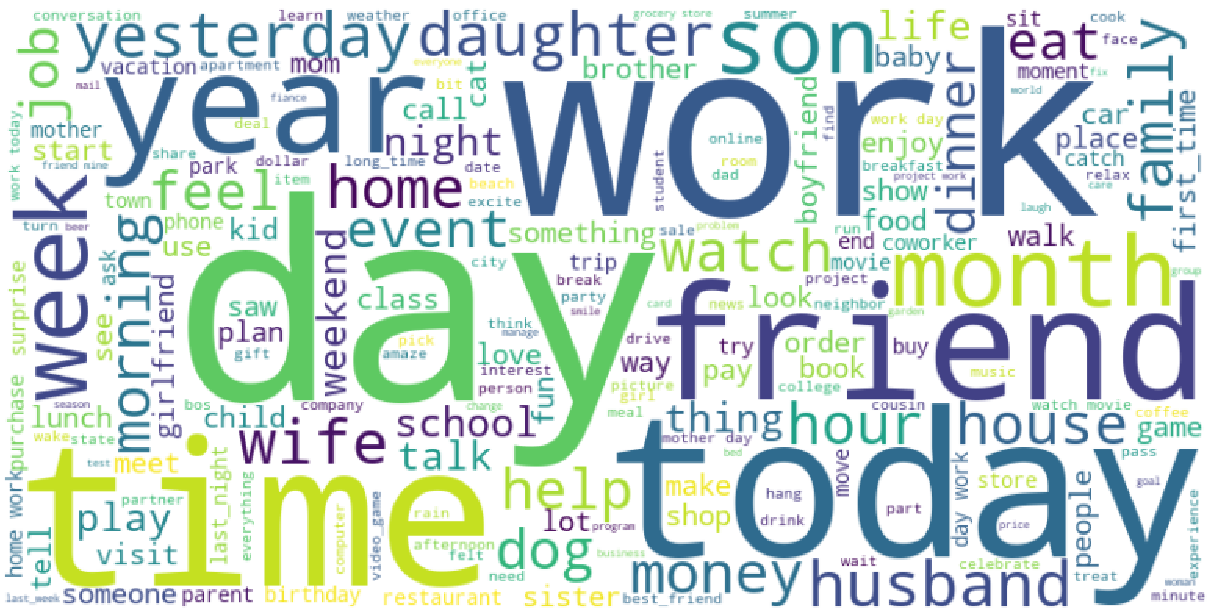


From the graph, it's evident that the USA and India have significantly more happy moments compared to all other countries, making them the primary contributors to the collected dataset. Due to the limited number of happy moments available from individuals in other countries, our analysis will primarily focus on understanding patterns within the USA and India.

In [614…

```
#Visulize WordCloud of USA and India
lemma_USA = lemma_demographic[lemma_demographic["country"]=="USA"]
USA_tokens = []
for token_list in lemma_USA["tokens"]:
    USA_tokens += token_list
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(" ".jo
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('WordCloud of USA', fontsize = 20, y = 1.1)
plt.show()

lemma_India = lemma_demographic[lemma_demographic["country"]=="IND"]
India_tokens = []
for token_list in lemma_India["tokens"]:
    India_tokens += token_list
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(" ".jo
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('WordCloud of India', fontsize = 20, y = 1.1)
plt.show()
```

WordCloud of USA



WordCloud of India

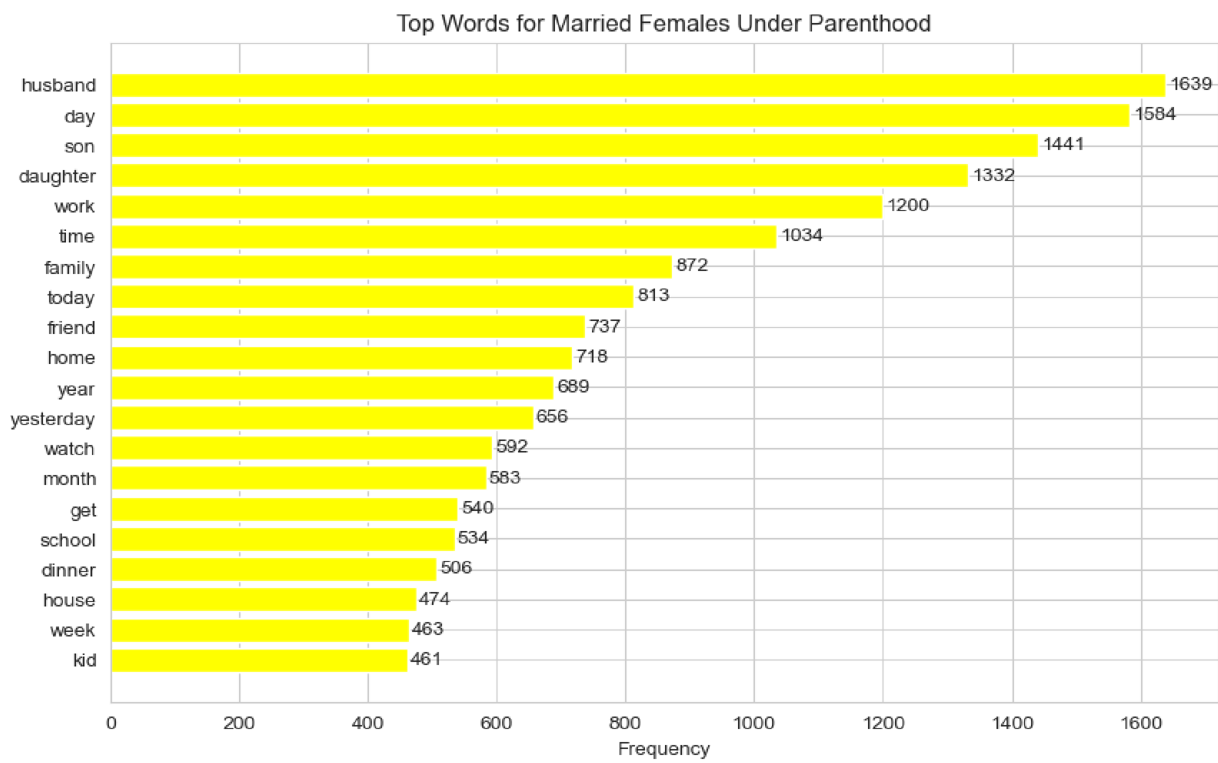
Apart from non-informative words, it's apparent that workers from the USA tend to discuss their work more frequently, whereas workers from India place a greater emphasis on their friends in their happy moments.

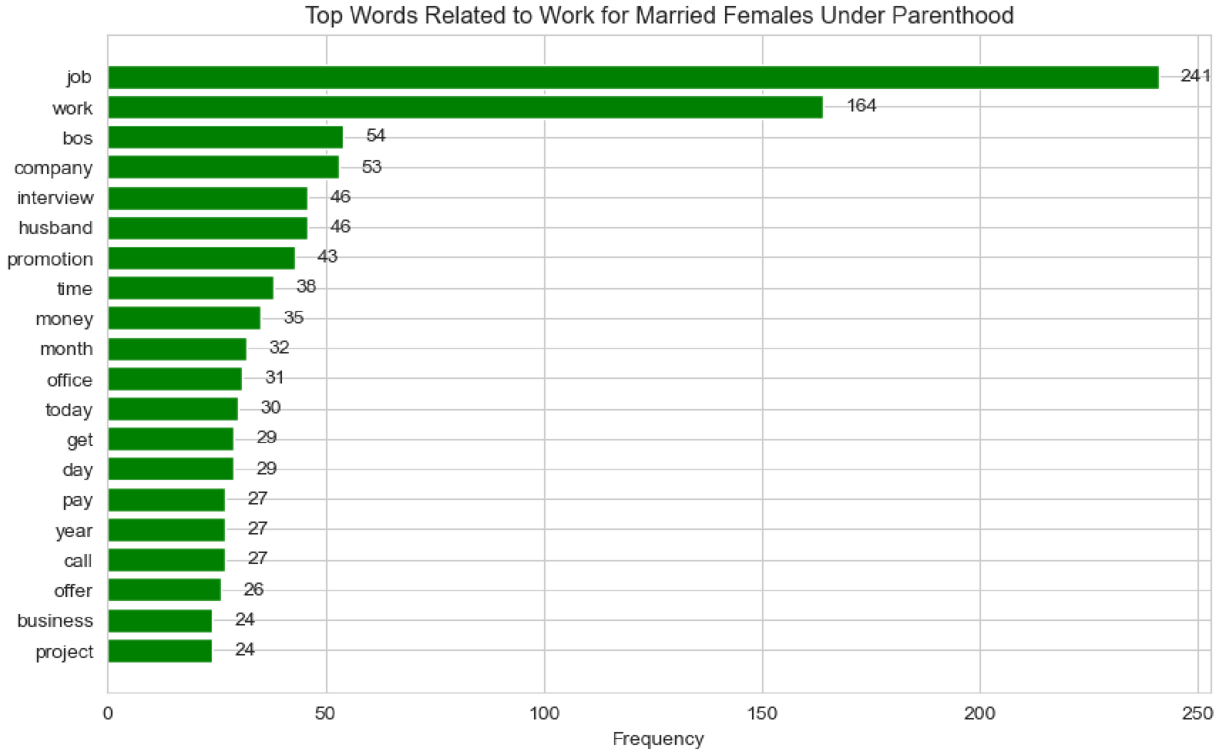
Family or work? (Analysis on married people with kids)

In [606…

```
married_female_tokens = lemma_demographic[(lemma_demographic["gender"]=="f")&(lemma_de
all_term_frequencies = Counter()
for tokens in married_female_tokens:
    all_term_frequencies += Counter(tokens)
top_words = all_term_frequencies.most_common(20)
```

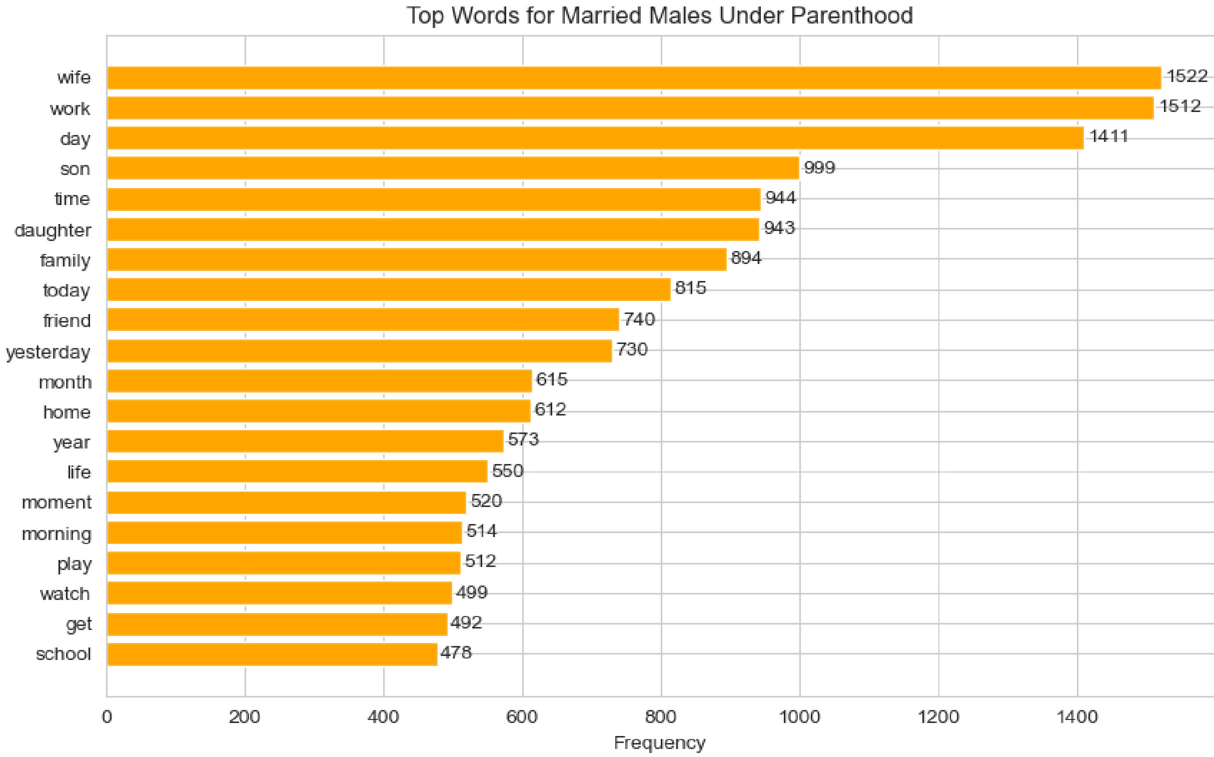
```
words, frequencies = zip(*top_words)

plt.figure(figsize=(10, 6))
bars = plt.barh(range(len(words)), frequencies, tick_label=words, color = "yellow")
plt.xlabel("Frequency")
plt.title("Top Words for Married Females Under Parenthood")
plt.gca().invert_yaxis()
for bar, freq in zip(bars, frequencies):
    plt.text(bar.get_width() + 5, bar.get_y() + bar.get_height() / 2, str(freq), va="c
plt.show()

married_female_work = work_topic[(work_topic["gender"]=="f")&(work_topic["marital"]=='
all_term_frequencies = Counter()
for tokens in married_female_work:
    all_term_frequencies += Counter(tokens)
top_words = all_term_frequencies.most_common(20)
words, frequencies = zip(*top_words)

plt.figure(figsize=(10, 6))
bars = plt.barh(range(len(words)), frequencies, tick_label=words, color = "green")
plt.xlabel("Frequency")
plt.title("Top Words Related to Work for Married Females Under Parenthood")
plt.gca().invert_yaxis()
for bar, freq in zip(bars, frequencies):
    plt.text(bar.get_width() + 5, bar.get_y() + bar.get_height() / 2, str(freq), va="c
plt.show()
```

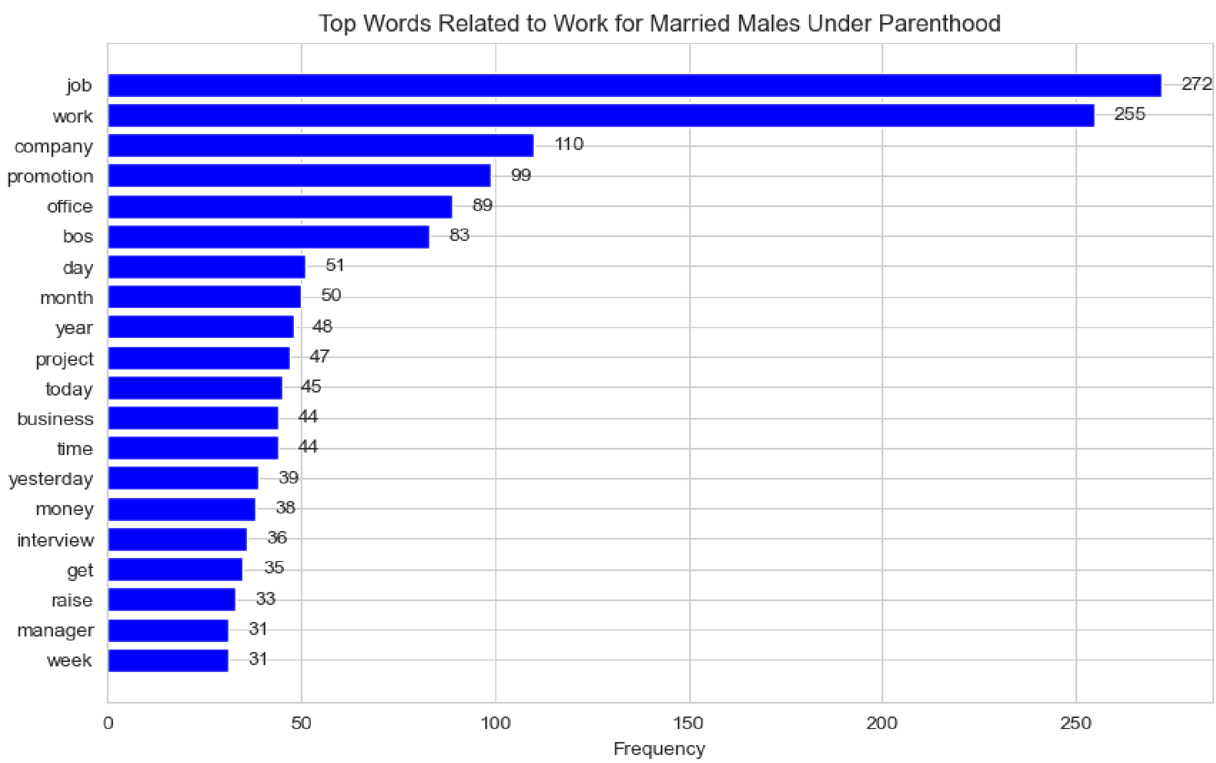




In [609…

```
married_male_tokens = lemma_demographic[(lemma_demographic["gender"]=="m")&(lemma_demo
all_term_frequencies = Counter()
for tokens in married_male_tokens:
    all_term_frequencies += Counter(tokens)
top_words = all_term_frequencies.most_common(20)
words, frequencies = zip(*top_words)

plt.figure(figsize=(10, 6))
bars = plt.barh(range(len(words)), frequencies, tick_label=words, color = "orange")
plt.xlabel("Frequency")
plt.title("Top Words for Married Males Under Parenthood")
plt.gca().invert_yaxis()
for bar, freq in zip(bars, frequencies):
    plt.text(bar.get_width() + 5, bar.get_y() + bar.get_height() / 2, str(freq), va="c
plt.show()

married_male_work = work_topic[(work_topic["gender"]=="m")&(work_topic["marital"]=="ma
all_term_frequencies = Counter()
for tokens in married_male_work:
    all_term_frequencies += Counter(tokens)
top_words = all_term_frequencies.most_common(20)
words, frequencies = zip(*top_words)

plt.figure(figsize=(10, 6))
bars = plt.barh(range(len(words)), frequencies, tick_label=words, color = "blue")
plt.xlabel("Frequency")
plt.title("Top Words Related to Work for Married Males Under Parenthood")
plt.gca().invert_yaxis()
for bar, freq in zip(bars, frequencies):
    plt.text(bar.get_width() + 5, bar.get_y() + bar.get_height() / 2, str(freq), va="c
plt.show()
```



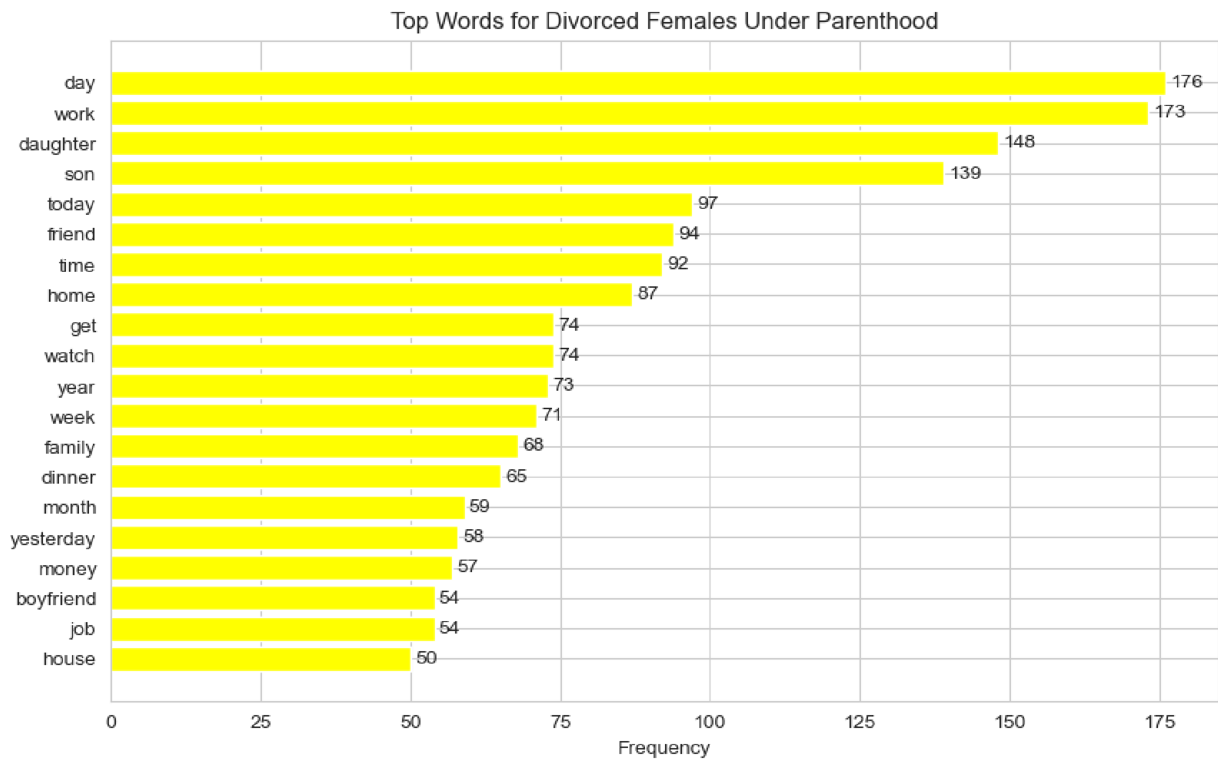


It's evident that married women with children often express their happiness by mentioning their kids and husbands more frequently than their work in their happy moments. Conversely, married men with children tend to discuss their wives and work more than their kids. Furthermore, when it comes to topics related to work, one of the most common themes in married women's happy moments is their husbands. However, husbands do mention their wives' work-related moments, but less frequently.

Family or Work? (Analysis on divorced people with kids)

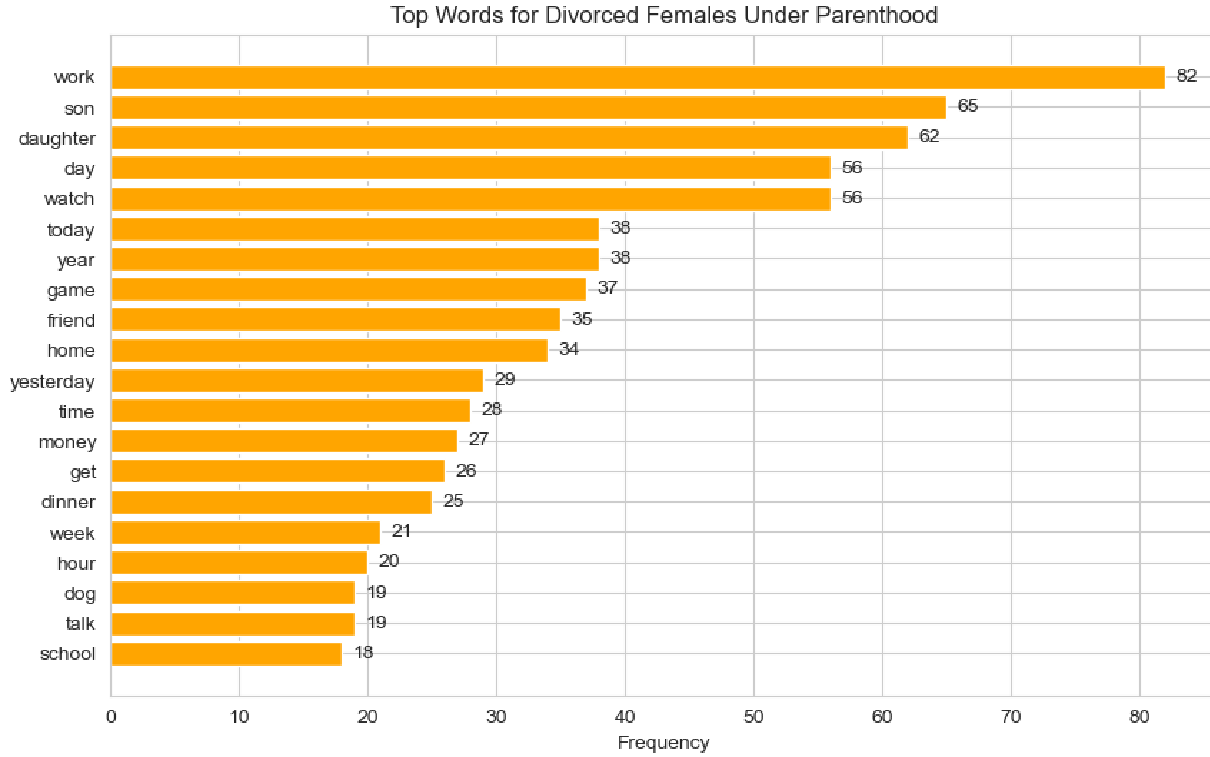
In [611…

```
divorced_female_tokens = lemma_demographic[(lemma_demographic["gender"]=="f")&(lemma_d
all_term_frequencies = Counter()
for tokens in divorced_female_tokens:
    all_term_frequencies += Counter(tokens)
top_words = all_term_frequencies.most_common(20)
words, frequencies = zip(*top_words)

plt.figure(figsize=(10, 6))
bars = plt.barh(range(len(words)), frequencies, tick_label=words, color = "yellow")
plt.xlabel("Frequency")
plt.title("Top Words for Divorced Females Under Parenthood")
plt.gca().invert_yaxis()
for bar, freq in zip(bars, frequencies):
    plt.text(bar.get_width() + 0.8, bar.get_y() + bar.get_height() / 2, str(freq), va=
plt.show()
```



In [612…

```
divorced_male_tokens = lemma_demographic[(lemma_demographic["gender"]=="m")&(lemma_dem
all_term_frequencies = Counter()
for tokens in divorced_male_tokens:
    all_term_frequencies += Counter(tokens)
top_words = all_term_frequencies.most_common(20)
words, frequencies = zip(*top_words)

plt.figure(figsize=(10, 6))
bars = plt.barh(range(len(words)), frequencies, tick_label=words, color = "orange")
plt.xlabel("Frequency")
plt.title("Top Words for Divorced Females Under Parenthood")
plt.gca().invert_yaxis()
for bar, freq in zip(bars, frequencies):
    plt.text(bar.get_width() + 0.8, bar.get_y() + bar.get_height() / 2, str(freq), va=
plt.show()
```



It's interesting to see that both divorced men and women often prioritize work as their primary source of happiness.