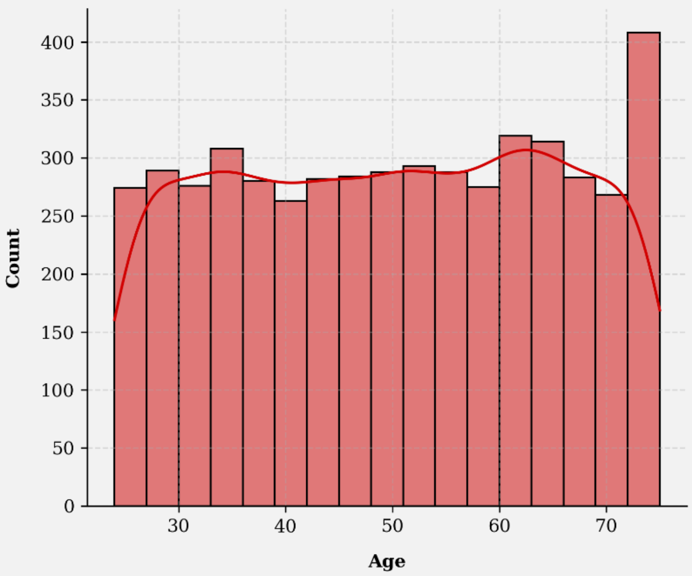
JCPenney | Data Insights and Next Steps Forward

1 | Understanding JCPenney Customers

Understanding the age demographic and product rating behaviour of JCPenney customers is critical for effective business strategy when targeting certain demographics and to highlight any issues with product quality alongside the supply chain.

Figure 1: Histogram with KDE curve showing age of JCPenney Users
KDE = Kernel Density Estimate



The data from **Figure 1** exhibits a relatively uniform distribution of JCPenney customers' ages from their early 20s up to the mid-60s, with a **peak among older customers (65-70+ years old).** While JCPenney attracts a range of ages, their customer data indicates they have a sizeable senior demographic.

This is understandable considering JCPenney stores were a common sight in the United States (US) shopping malls in the early 2000s, and the data likely represents those now senior customers who remain loyal to JCPenney to this day.

Looking at **Figure 2,** the heatmap colour gradient indicates how differently age brackets review and score all JCPenney products. This pattern suggests that while certain age groups show a slight preference for extreme ratings (e.g. 21.6% of 18–24-year-olds score JCPenney products 1 out of 5), the overall mix of feedback is **very consistent across all age demographics in the data.**

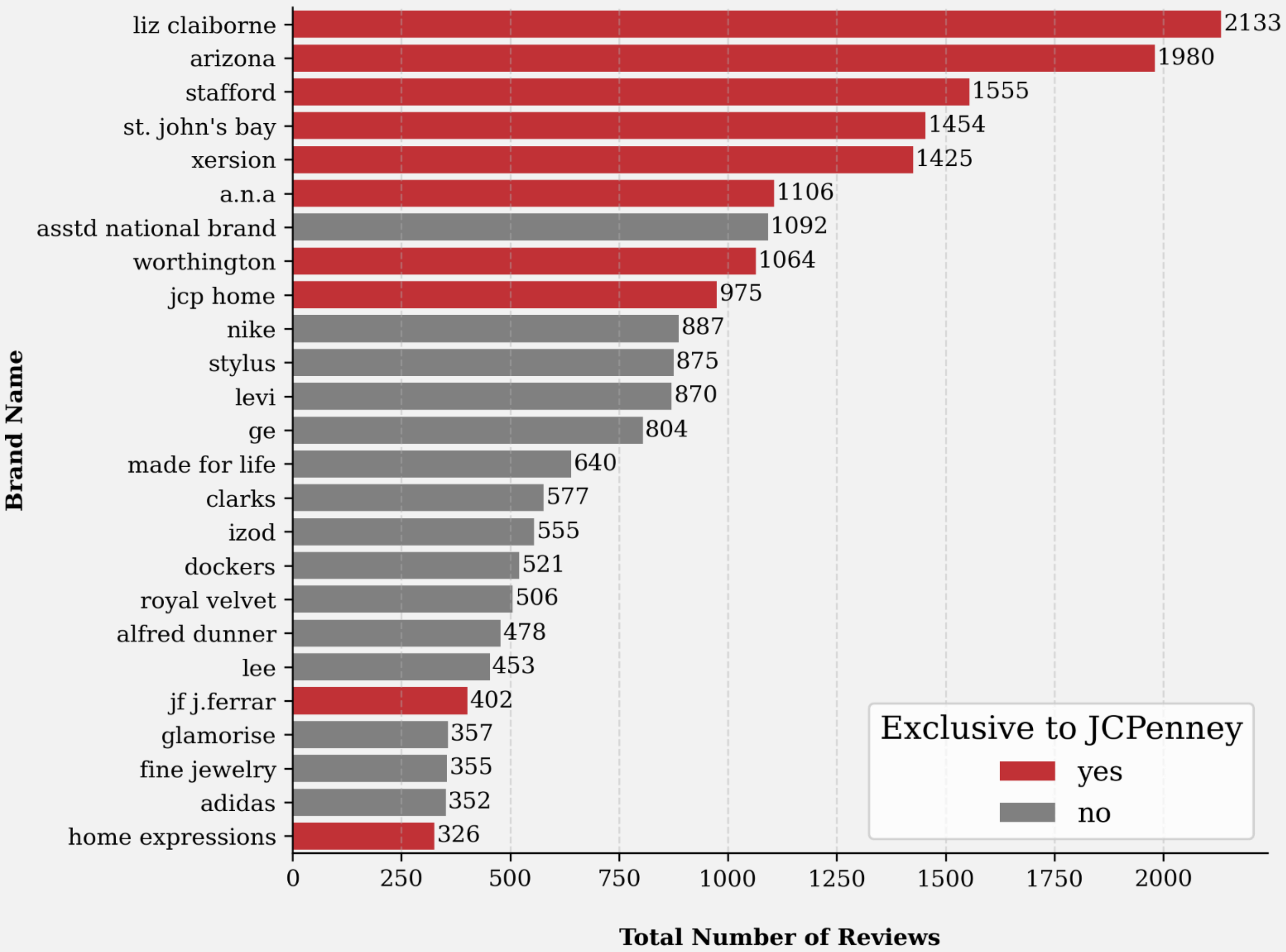
It is important to consider that these metrics are across 39,000 total reviews, so nuances may be diluted by the large sample size.

Figure 2: Heatmap of Review Score Distribution by Age Category. Normalised % calculated by dividing number of reviews per score by total number of people in age category.

2 | JCPenney Private Brand Performance

Customers will assess their loyalty to retail companies based on the quality of their **exclusive/private brands**. JCPenney owns a wide variety of exclusive brands (such as *Stafford* and *Liz Claiborne*), allowing them full control to develop and tailor these products to specific customer demographics and oversee their supply chains to ensure production quality is upheld throughout the US.

Figure 3: Bar plot showing Top 25 brands at JCPenney by number of reviews received on their products.



NOTE: 'Asstd national brand' refers to a selection or mix of products from various well-known, manufacturer-owned brands

Figure 3 shows that of the 25 most-reviewed brands by JCPenney customers, **40% are JCPenney exclusive bands.** The most popular private brand by ratings '**Liz Claiborne' has more than double the number of reviews** as the most popular non-exclusive brand 'Nike' (2133 vs. 887). This indicates JCPenney exclusive brands have **strong visibility** to their customers when compared to non-exclusive brands and **their marketing strategies has proven very effective to differentiate JCPenney exclusive bands** from other top-performing brands with a loyal customer base, such as Nike and Levi.

While it is important JCPenney's private brands are among the most-reviewed brands, it's important to ensure their products are reviewed highly against other brands.

Figure 4: Bar plot showing JCPenney Private Brands Average Review Rating across all their respective products. Bars coloured if they scored above (red) or below (grey) the review rating across all brands stocked at JCPenney.

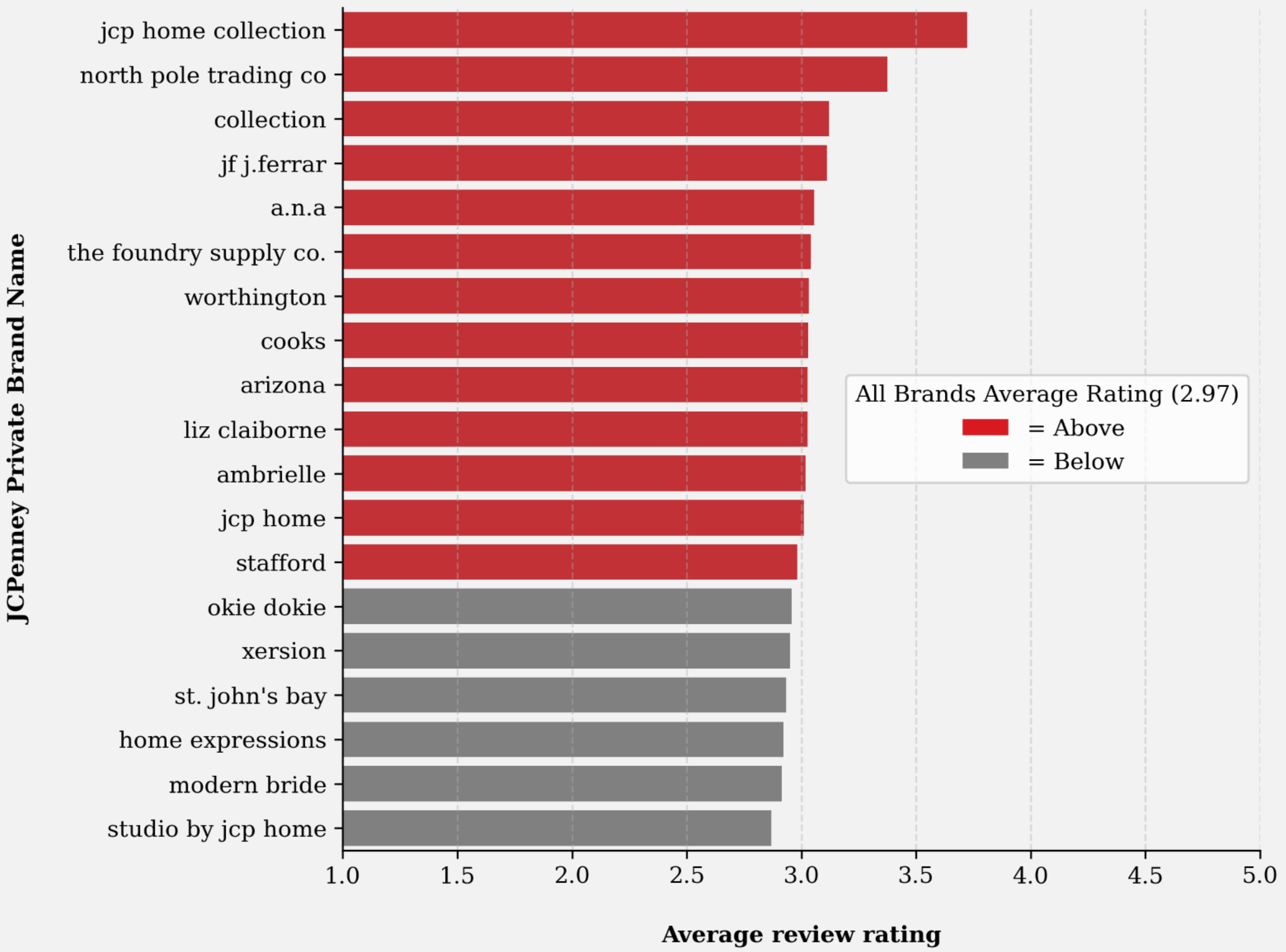


Figure 4 displays the 19 JCPenney private brands found in the data, alongside their average review rating for their products. **68.4% of JCPenney exclusive brands have a higher average review rating in comparison to the average rating across all brands stocked in JCPenney stores.** As a chain is only as strong as its weakest link, therefore it imperative to investigate JCPenney brands like 'Xersion' and 'Home Expressions' who seem to be underperforming.

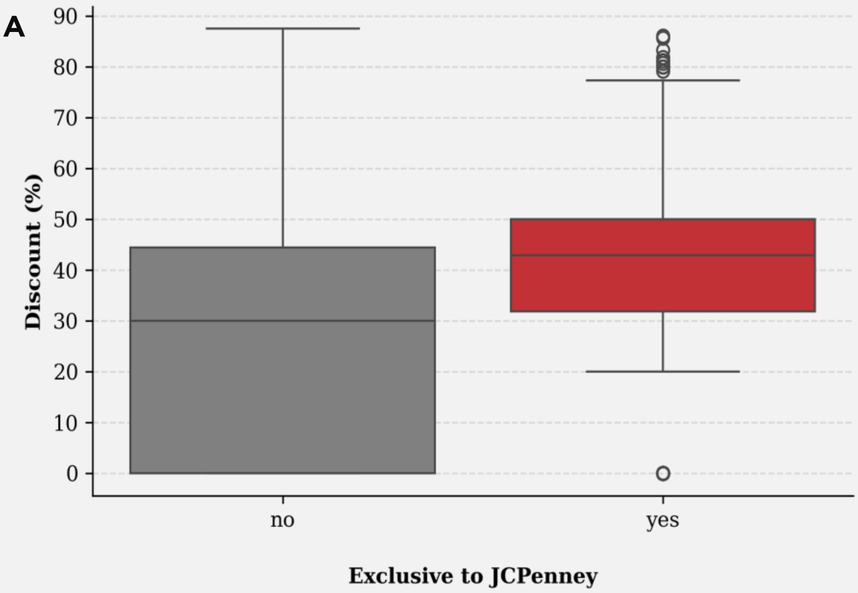
Crucially, this may give insight into the **changing customer demographics** for JCPenney brands. For example, 'Modern Bride' specialises in wedding & engagement rings. Underperformance could be a result of not appealing to the new generation (Gen-Z) of marrying couples.

3 | Impact of Discounting on Brands and Products

Providing a discount on selected products is among the most effective strategies a retailer can use to sell more inventory and build brand loyalty. It can however cause long-term damage to brands by lowering the perceived value their products, if discounting is too frequent.

Figure 5: A) Box Plot and B) Summary Table Comparing Discount percentage (%) for Exclusive (red) and Non-Exclusive (grey) JCPenney Brands

A



B

count	mean	std	min	25%	50%	75%	max
4256.0	27.3	22.0	0.0	0.0	30.0	44.5	87.5
1604.0	38.7	21.7	0.0	31.8	42.9	50.1	86.1

In relation to JCPenney exclusive brands, the boxplot and summary table in **Figure 5** compares discount percentages between JCPenney's Exclusive Brands (Red) and Non-Exclusive Brands (Grey). We see exclusive brands show a significantly higher mean discount of **38.7%** compared to **27.3%** for non-exclusive brands. Although **the maximum, minimum,** and **overall spread (standard deviation)** of discounts **are about the same for both exclusive and non-exclusive brands**, the key takeaway is the Interquartile Range (IQR)**.**

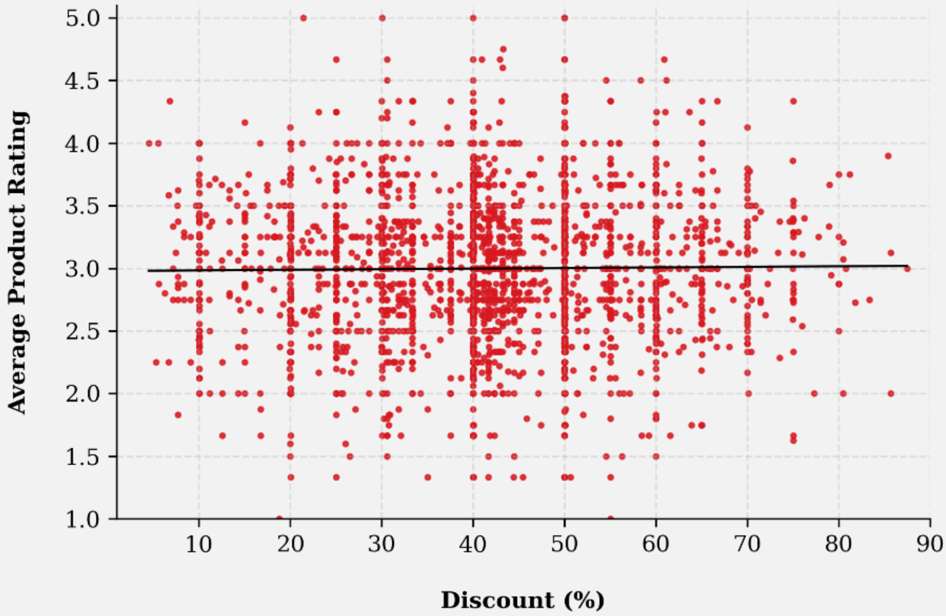
IQR describes how **consistent** the discounts are for the middle 50% (i.e. 75% - 25%) of all reviewed products for each group. Exclusive JCPenney brands have a low IQR of 18.3%, **indicating products are predictably discounted at its higher discount rate** while non-exclusive brands have a larger IQR of 44.5%, highlighting **discounts rates are volatile and inconsistent.** These findings reveal **JCPenney heavily relies on discounting their exclusive products** likely to shift inventory faster and try to compete with non-exclusive brands which have dedicated and loyal customers, such as 'Ralph Lauren' and 'Adidas'.

On the other hand, it's valuable to understand whether increasing the discount % on products will have any effect on the rating left by JCPenney customers. **Figure 6** displays all JCPenney products with their respective positions plotted based on **their average product rating vs. the discount % they were sold at.**

JCPenney products are **widely scattered** across the regression plot with most products falling within the average rating range of 2.0 – 4.0. Visually, the **flat** black linear regression line indicates discount % has little predictive power over the average product rating.

Furthermore, statistical analysis confirmed **no statistically significant relationship between discount percentage and average product rating** (r = 0.012, p = 0.526). In other words, whether products have a 10% discount or an 80% discount, the customer's perception of the product quality does not change.

Figure 6: A) Regression Plot Showing Average Product Rating Versus Discount Percentage across all products at JCPenney. Black line shows linear regression line, only products for which discount % > 0.



Summary of Results and Next Steps

- The customer age distribution is relatively uniform from the early 20s up to the mid-60s, with a **slight peak among older customers (65-70+ years old).** JCPenney should ensure their **product services are accessible** (avoid gamified or digital-only programs) to maintain their senior customers loyalty.
- The overall mix of scoring feedback is similar across all age demographics – however, this is likely due to **smoothing by the large sample size.** Further analysis is needed into **each age category separately, across different product categories** to reveal nuances in product scoring.
- JCPenney's exclusive brands have strong visibility to their customers, accounting for **40%** of the 25 most-reviewed brands in JCPenney stores. **68.4%** of JCPenney exclusive brands have an **average review rating higher** than the average rating across all brands stocked by JCPenney,
- Underperforming JCPenney exclusive brands like 'Xersion,' and 'Modern Bride' should be investigated **by analysing the customer product reviews** (e.g. sentiment analysis) **or performing internal audits on product quality** to ensure supply chains are consistent**.** The root cause may also be failure to appeal to a changing customer demographic (e.g. Gen-Z).
- Exclusive JCPenney brands also show a **significantly higher mean discount of 38.7%** compared to 27.3% for non-exclusive brands. There is **no statistically significant relationship** between discount percentage and average product rating.
- JCPenney should investigate **the frequency of discounts offered on their exclusive brands over time** to avoid causing long-term damage to the perceived value of their brands.

Appendix

0) Setup

Import Python Libraries to explore and visualise data

In [1]:
```
import os
###### for data manipulation #####
import pandas as pd
import numpy as np
import datetime
from scipy.stats import pearsonr
##### for data visualisation #####
import matplotlib.pyplot as plt
from matplotlib.patches import Patch
from matplotlib import rc
import seaborn as sns
plt.style.use('default')
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

In [2]:
```
##### colour code for visualisations #####
penney_red = '#D91920'
#### set figure font ####
plt.rcParams["font.family"] = "serif"
```

JCPenney Data:

There are 5 files given: `products.csv`, `users.csv`, `reviews.csv`, `jcpenney_reviewers.json`, `jcpenney_products.json`

Let's **import** the data and understand what information we have!

In [3]:
```
# filepath to folder containing JCPenney data
directory = "C:/Users/Darragh/Desktop/RMData/jcpenney"   #change if necessary

# list of file names in JCPenney folder to load in`
files = ['products.csv', 'users.csv', 'reviews.csv',
         'jcpenney_reviewers.json','jcpenney_products.json']
```

Load in JCPenney data (using `read_csv()` and `read_json()`) into a dataframe (df). Then store in a dictonary for easy access later.

In [4]:
```
# initialise dictionary
jcpenney_dfs = {}

for file_name in files:
    path = os.path.join(directory, file_name) # Store path to file

    # Load .csv file as df and add to dictionary (key = file_name)
    if file_name.endswith('.csv'):
         jcpenney_dfs[file_name] = pd.read_csv(path)

    #^same as before but for .json files
    elif file_name.endswith('.json'):
        jcpenney_dfs[file_name] = pd.read_json(path, lines = True)
                #each line in .json file is a json object^^

# check files have been added correctly
print(f'jcpenney_dfs = {list(jcpenney_dfs)}')
```

```
jcpenney_dfs = ['products.csv', 'users.csv', 'reviews.csv', 'jcpenney_reviewers.json', 'jcpenney_products.json']
```

We can access any file's df using the following: `df = jcpenney_dfs[file_name]`

---

1) Explore the data

In [5]:
```
# Check number of row/columns and column names in each file
for file_name, df in jcpenney_dfs.items():
    rows, cols = df.shape
    column_names = ', '.join(df.columns)

    print(f"\n{file_name} -- {rows} rows and {cols} columns")
    print(f"Columns: {column_names}")
```

```
products.csv -- 7982 rows and 6 columns
Columns: Uniq_id, SKU, Name, Description, Price, Av_Score

users.csv -- 5000 rows and 3 columns
Columns: Username, DOB, State

reviews.csv -- 39063 rows and 4 columns
Columns: Uniq_id, Username, Score, Review

jcpenney_reviewers.json -- 5000 rows and 4 columns
Columns: Username, DOB, State, Reviewed

jcpenney_products.json -- 7982 rows and 15 columns
Columns: uniq_id, sku, name_title, description, list_price, sale_price, category, category_tree, average_product_r
ating, product_url, product_image_urls, brand, total_number_reviews, Reviews, Bought With
```

First let's explore data relating to JCPenney customers age and review scores

In [6]:
```
#Load in jcpenney_products.json + users.csv  dfs
df = jcpenney_dfs['jcpenney_products.json'].copy()
df_user = jcpenney_dfs['users.csv'].copy()

#Review column in jcpenney_products.json contains list of dictonaries of Username, Review and Score
#Convert nested dictonary to df, save as df_score

df_score = pd.json_normalize(    #.explode() creates new row for each item in Review column
    df['Reviews'].explode() )    # .json_normalize() flattens them horizontally into `score_df`

#show
display(df_score.head(1))
display(df_user.head(1))
```

	User	Review	Score
0	fsdv4141	You never have to worry about the fit...Alfred...	2

	Username	DOB	State
0	bkpn1412	31.07.1983	Oregon

In [7]:
```
# Convert df_score data types: User -> str
df_score['User'] = df_score['User'].astype('string')

# Convert user.csv data types: Username -> str //   DOB -> datetime
df_user['Username'] = df_user['Username'].astype('string')
df_user['DOB'] = pd.to_datetime(df_user['DOB'])

#rename column username -> user to join df_score with df_user
df_user = df_user.rename(columns ={'Username':'User'})
```

In [8]:
```
#create new age column from DOB
today = datetime.date.today()
df_user['Age'] = ((today - df_user['DOB'].dt.date) / pd.Timedelta(days=365.25)
    ).round().astype(int)                                   #^account for leap years
```

Next, we will categories user's age into Age Categories 18-24, 25-34, 35-44, 45-54, 55-64, 65+

In [9]:
```
#Create bins and labels for age categories
bins = [18,25,35,45,55,65,80]
age_cat = ['18-24','25-34','35-44','45-54','55-64','65+']
```

```
#creating age category column from 'Age' column, using pd.cut()
#right=false to ensure boundary ages e.g. 25 are include in correct 25-34 bin
df_user['Age_Category'] = pd.cut(df_user['Age'],
                              bins=bins,
                              labels=age_cat,
                              right=False)

#ensure categories are ordered for sorting and plotting
df_user['Age_Category'] = df_user['Age_Category'].astype(
    pd.CategoricalDtype(categories=age_cat, ordered=True))
```

In [10]:
```
# inner join on 'user' between df_user and df_score,
# return new df called `df_userscore`
df_userscore = pd.merge(df_user, df_score, on='User', how = 'inner')

print(df_userscore.info())
#display(df_userscore.head(1))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39080 entries, 0 to 39079
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   User          39080 non-null  string
 1   DOB           39080 non-null  datetime64[ns]
 2   State         39080 non-null  object
 3   Age           39080 non-null  int64
 4   Age_Category  39080 non-null  category
 5   Review        39080 non-null  object
 6   Score         39080 non-null  int64
dtypes: category(1), datetime64[ns](1), int64(2), object(2), string(1)
memory usage: 1.8+ MB
None
```

`df_userscore` contains all 39080 review scores + user information (age, age_category etc.)

Figure 1

Histogram with a Kernel Density Estimate (KDE) Curve showing JCPenney Customer ages

- KDE curve will provide an easy visual of age distribution, including any peaks in certain age brackets.
- Alternatives considered were a pie chart but this felt inferior as it's difficult to compare age categories like a histogram.

In [11]:
```
#Filter `df_userscore` for 'user', 'age' + 'age_category'
plot_age = df_userscore[['User','Age','Age_Category']]

#drop duplicates
plot_age = plot_age.drop_duplicates()
print(f'Rows after dropping dups: {len(plot_age)}')
```

```
Rows after dropping dups: 4994
```

In [12]:
```
#check if any users appear more than once
plot_age['User'].value_counts().head(2)
```

Out[12]:
```
User
dqft3311    2
czof3441    1
Name: count, dtype: Int64
```

USER dqft3311 appears more than 1 with different DOB, we will remove this user from further analysis

In [13]:
```
#update df to remove user 'dqft3311'
plot_age = plot_age[plot_age['User']!= 'dqft3311']
```

In [14]:
```
#figure specs
plt.figure(figsize = (6,5))#, dpi = 300)

#plotting and coloring graph data
#assign to 'ax' to change figure layout (below)
ax = sns.histplot(x=plot_age['Age'],
        bins = 'auto',
```

```
        kde = True,
        color = '#D20001',
        edgecolor='black')

#remove right and top axes borders
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)


#axis labels + spacing, grid settings
plt.xlabel('Age', fontweight = 'bold', labelpad = 10)
plt.ylabel('Count', fontweight = 'bold', labelpad = 10)
plt.grid(linestyle = '--', alpha = 0.4)

#plt.savefig('Hist_of_age.png', transparent = True)
plt.show()
```

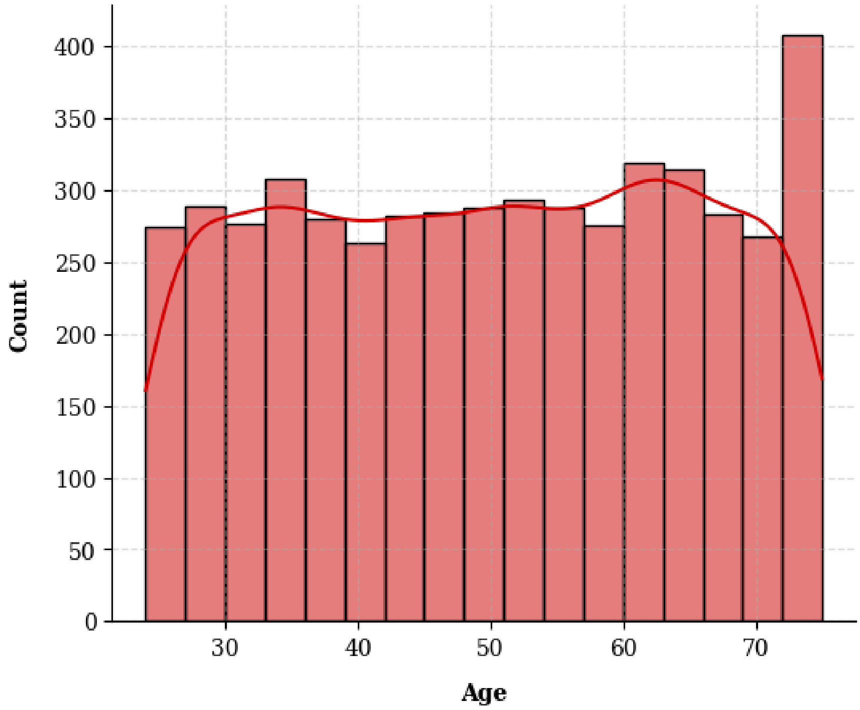


Figure 2

Heatmap for % of scores given by an age category (normalised percentage calculated by dividing total times a score was given by total category population x 100)

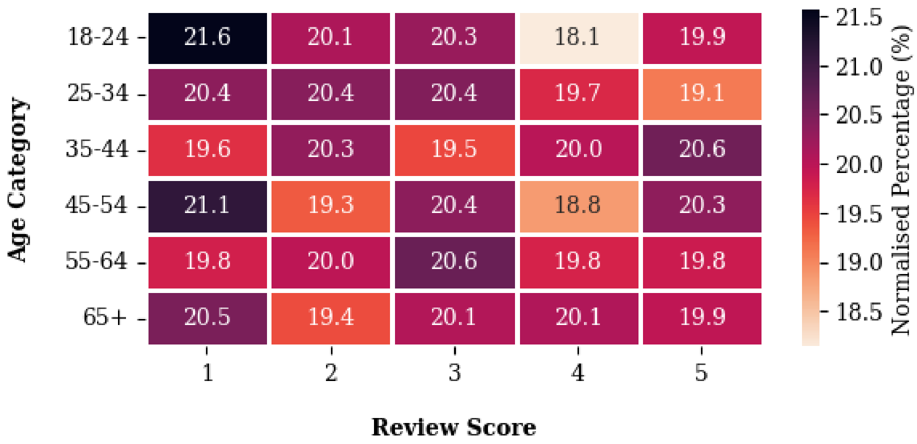
- Provides a visually pleasing snap shot to compare how each age category scores JCPenney products
- Alternative visuals considered were stacked bar chart however elected to choose heatmap for a business report as colour change indicates difference in % of scores given rather than purely a difference between age category

In [15]:
```
#use .crosstab() to calculate total number of each score given
#by age category
rating_by = pd.crosstab(index=df_userscore['Age_Category'],
                        columns=df_userscore['Score'])
display(rating_by)
```

Score	1	2	3	4	5
Age_Category					
18-24	132	123	124	111	122
25-34	1542	1545	1549	1492	1447
35-44	1426	1475	1413	1453	1495
45-54	1579	1443	1521	1407	1520
55-64	1543	1556	1608	1540	1547
65+	1715	1625	1678	1680	1669

In [16]:
```
#Sum the total across rows horizontally (hence axis=1)
row_sums = rating_by.sum(axis=1)
#divide value in cell by row_sums total from previous and x100 for %
rating_by_norm = rating_by.div(row_sums, axis=0) * 100
```

In [17]:
```
#Figure specs
plt.figure(figsize=(6, 3))#, dpi = 300)

#plotting data and coloring heatmap
sns.heatmap(
    rating_by_norm,
    annot=True,
    fmt=".1f",
    cmap="rocket_r",
    linewidths=1,
    cbar_kws={'label': 'Normalised Percentage (%)'}
)

#axis labels and spacing
plt.xlabel('Review Score', fontweight = 'bold',labelpad = 15)
plt.ylabel('Age Category', fontweight = 'bold',labelpad = 15)
plt.tight_layout()

#plt.savefig('review_score_heatmap.png', transparent = True)
plt.show()
```



Next, Lets check total and average score reviews for all JC Penney products

In [18]:
```
# get jcpenney_products.json df
df= jcpenney_dfs['jcpenney_products.json'].copy()

#show first 2 rows
display(df.head(2))
```

	uniq_id	sku	name_title	description	list_price	sale_price	category	category_
0	b6c0b6bea69c722939585baeac73c13d	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	You'll return to our Alfred Dunner pull-on cap...	41.09	24.16	alfred dunner	jcpenney|women|a du
1	93e5272c51d8cce02597e3ce67b7ad0a	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	You'll return to our Alfred Dunner pull-on cap...	41.09	24.16	alfred dunner	jcpenney|women|a du

We see multiple rows for the same `product`, therefore we need to collate data so each product has it's own row.

We first filter for the columns needed:

- `sku` (Stock Keeping Unit) - Unique identifier for products
- `average_product_rating`
- `total_number_reviews`.

And clean up data (e.g. remove rows with empty sku's, and keep plausible results (rating 1-5))

In [19]:
```
# filter columns
df = df[['sku','average_product_rating','total_number_reviews']]
print(f'Starting rows: {len(df)}')

# remove rows with empty sku entries
df = df[ df['sku'] != '']
print(f'Remove empty sku entries, rows left: {len(df)}')

#keep ratings 1-5 only
df = df[df['average_product_rating'].between(1,5)]
print(f'Keep ratings between 1-5, rows left: {len(df)}')
```

```
Starting rows: 7982
Remove empty sku entries, rows left: 7915
Keep ratings between 1-5, rows left: 7915
```

Next we group rows by `sku` (using `.groupby`) and calculate the true `average_product_rating` and `total_number_reviews` for each product (using `.agg()`).

In [20]:
```
##.agg(new_column_name =('prev_column_name', 'calculation_peformed')
# return as new df, `df_sku_stats`
df_sku_stats = df.groupby('sku').agg(
    average_product_rating = ('average_product_rating','mean'),
    total_number_reviews = ('total_number_reviews', 'sum'))

#reset index so sku can be accessed for queries
df_sku_stats = df_sku_stats.reset_index()

#show df head
display(df_sku_stats.head(2))
```

	sku	average_product_rating	total_number_reviews
0	0903a80	2.9375	16
1	13cab12	2.8750	16

In [21]:
```
#check each row if sku are unique
sku_unique = df_sku_stats['sku'].nunique() == len(df_sku_stats)
print(sku_unique)
```

```
True
```

`df_sku_stats` contains product `sku` with their respective `average_product_rating` and `total_number_review`.

Looking at brand insights

While JCPenney does offer products from a variety of brands seen in other stores (e.g. Nike), they have their own private brands/labels that are sold exclusively in JCPenney stores.

- Let's take a look at how JCPenney private brands compare to other brands..

Sourced JCPenney Private Brands from (https://trademarks.justia.com/owners/j-c-penney-private-brands-inc-7136)

In [22]:
```
#list of jcpenney private brands
jcp_private_brands = [
    "St. John's Bay", "Arizona",
    "Xersion", "Worthington",
    "a.n.a", "Ambrielle", "Liz Claiborne",
    "Stafford", "JF J.Ferrar", "Collection",
    "The Foundry Supply Co.", "Okie Dokie",
    "JCP Home", "JCP Home Collection",
    "Studio by jcp home", "Cooks",
    "Home Expressions", "North Pole Trading Co",
    "Modern Bride"]

#convert list items to lowercase
#for easier merging/checking with other dataset
jcp_private_brands = [i.lower() for i in jcp_private_brands]
```

In [23]:
```
#load `jcpenney_products.json` df
df = jcpenney_dfs['jcpenney_products.json'].copy()

#filter columns
df = df[['sku','brand']]

#convert column datatype, 'sku' and 'brand' --> str
df['sku'] = df['sku'].astype('string')
df['brand'] = df['brand'].astype('string')

#convert brands to lowercase for ease when merging together
#in the case same brands are spelt with/without capitals
df['brand'] = df['brand'].str.lower()
```

Clean up df by removing rows with empty `sku` entries + removing duplicate rows with same `sku` and `brand`

In [24]:
```
#show starting no. rows in df
print(f'Starting rows = {len(df)}')

#drop empty sku rows
df = df[ df['sku'] != '']
print(f'Removing empty sku entries, Rows = {len(df)}')

#drop rows with same sku and same brand
df = df.drop_duplicates()
print(f'Removing duplicate entries, Rows = {len(df)}')
```

```
Starting rows = 7982
Removing empty sku entries, Rows = 7915
Removing duplicate entries, Rows = 6045
```

In [25]:
```
# Check if the number of unique SKUs equals the total number of rows
# i.e. are all sku associated with only 1 brand?
sku_unique = df['sku'].nunique() == len(df)
print(sku_unique)
```

```
False
```

Since result is FALSE, we need to check which sku are associated with multiple brands and correct it appropriately

In [26]:
```
#group by sku and filter for sku's with >1 brand associated
find_sku = df.groupby('sku')['brand'].nunique()
dup_brand = find_sku[find_sku>1].index

#return df (dup_df) to check position of multi-brand associated skus
dup_df = df[ df['sku'].isin(dup_brand)].copy()
dup_df.head()
```

Out[26]:

	sku	brand
522	pp5005280084	jcp home
7648	pp5002940877	studio by jcp home
7731	pp5002940877	studio
7739	pp5005280084	jcp home collection

`sku` pp5002940877 + pp5005280084 are associated with multiple brands, however seems to be different wordings for a similar brand

- Let's check which brand wording appears most frequently and remove the least frequent occurrence.

In [27]:
```
#Finding freq of all brands
all_brands = df['brand'].value_counts()

# get brands which appear with multiple sku (dup_df)
# and find how often they occur
conflict_brands = dup_df['brand'].unique()
freq = all_brands.loc[conflict_brands]

print(freq.sort_values(ascending=False))
```

```
brand
jcp home               102
studio by jcp home       8
jcp home collection      3
studio                   2
Name: count, dtype: Int64
```

Appears `studio`, `jcp home collection` are the least frequent occurring, therefore we will remove these version of the sku

In [28]:
```
#Let's remove entries by their index (7731 + 7739)
print(len(df))
df.drop(labels=[7731,7739], inplace=True)
print(f'{len(df)}, 2 entries successfully removed')
```

```
6045
6043, 2 entries successfully removed
```

In [29]:
```
# Again, check if unique SKUs are associate with 1 brand only
sku_unique = df['sku'].nunique() == len(df)
print(sku_unique)
```

```
True
```

Now that the result is TRUE, we can continue with the data now each `sku` is associated with a single `brand`

Now we can add in a column to show which brands are JCPenney exclusives!

In [30]:
```
# Create new column 'exclusive_to_jcpenney', using .npwhere()
#if brand matches any brand found in list 'jcp_private_brands'
# entry will be 'yes' and 'no' if not.
df['exclusive_to_jcpenney'] = np.where(
    df['brand'].isin(jcp_private_brands),
                        'yes',
                        'no')

#Set sku as index and save df as `df_brands` for later
df_brands = df.set_index('sku')
```

`df_brands` contains product `sku` with respective `brand` and whether or not they are `exclusive_to_jcpenney`

Merge dfs `df_sku_stats` with `df_brands` to get stats about each brand

In [31]:
```
#Check number of rows in each df
display(df_sku_stats.head(1))
print(f'df_sku_stats rows: {len(df_sku_stats)}')

display(df_brands.head(1))
print(f'df_brands rows: {len(df_brands)}')
```

	sku	average_product_rating	total_number_reviews
0	0903a80	2.9375	16

```
df_sku_stats rows: 6043
```

	brand	exclusive_to_jcpenney
sku		
pp5006380337	alfred dunner	no

```
df_brands rows: 6043
```

Both dfs have same number of rows, let's merge them together!

In [32]:
```
#Merge dfs using Inner join on the sku
df = pd.merge(df_sku_stats, df_brands, on='sku', how = 'inner')
```

In [33]:
```
#check rows after merge
print(f'Number of rows: {len(df)}')

#save df as df_brand_stats
df_brand_stats = df.copy()
df_brand_stats.head(1)
```

```
Number of rows: 6043
```

Out[33]:

	sku	average_product_rating	total_number_reviews	brand	exclusive_to_jcpenney
0	0903a80	2.9375	16	kitchen aid	no

Next we group data by brand (using `.groupby()`) to get insights on individual brand performance using `.agg()` , same as before for `df_sku_stats` !

In [34]:
```
#.agg(new_column_name =('prev_column_name', 'calculation_peformed')
#Then save df as `group_brand_stats' for future recall
group_brand_stats = df_brand_stats.groupby('brand').agg(
    average_rating=('average_product_rating', 'mean'),
    total_reviews=('total_number_reviews', 'sum'),
    number_of_products=('sku', 'count'),
    exclusive_to_jcpenney=('exclusive_to_jcpenney', 'first')
)            #'first' will retain exclusivity status in agg. df
             # as all brand products are labelled the same

display(group_brand_stats.head(2))
print(f'Number of brands: {len(group_brand_stats)}')
```

	average_rating	total_reviews	number_of_products	exclusive_to_jcpenney
brand				
1928 jewelry	4.750000	3	2	no
a.n.a	3.056643	1106	126	yes

```
Number of brands: 711
```

Lets visualise data to see specific brand performance

- Because we don't want brands/products with low numbers of reviews skewing results, we should filter to **only include brands with >5 reviews.**

In [35]:
```
#Filter for 'total_reviews' >=5, save as plot_brand for later recall
plot_brand = group_brand_stats[group_brand_stats['total_reviews']>=5]

#confirming number of removed rows
print(f'''{len(group_brand_stats)-len(plot_brand)} brands have less than 5 reviews.
Brands remaining: {len(plot_brand)}''')

#show 2 rows plot_brand df
display(plot_brand.head(2))
```

```
234 brands have less than 5 reviews.
Brands remaining: 477
```

	average_rating	total_reviews	number_of_products	exclusive_to_jcpenney
brand				
a.n.a	3.056643	1106	126	yes
a2 by aerosoles	3.209722	118	15	no

Figure 3

TOP 25 BRANDS by BY TOTAL NUMBER OF REVIEWS

- Horizontal Barplot seems most reasonable visual as brand names will be very readable on y-axis (rather than vertical barplots x-axis with rotation) + easier to follow annotated number of total reviews along the bar

In [36]:
```
#sort plot_brand df by highest'average_rating' and take top 25 results
top_25_brands = plot_brand.sort_values(by = 'total_reviews', ascending = False).head(25)
```

In [37]:
```
#figure specifications
plt.figure(figsize = (8,6))#, dpi = 300)

#plotting and coloring graph data
#assign to 'ax' to change figure layout (below)
ax = sns.barplot(
    data=top_25_brands,
    x='total_reviews',
    y='brand',
    hue = 'exclusive_to_jcpenney',  #color by exclusivity
    palette= (penney_red, 'grey')
)

#set legend title and fontsize
ax.legend(fontsize=12, title_fontsize=14,
    title = "Exclusive to JCPenney")

#remove right and top axes borders
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

#annoate bars with corresponding value
for bar in ax.containers:
    ax.bar_label(bar, color = 'black', padding=1)

#set axis labels and grid layout
ax.set_xlabel('Total Number of Reviews', fontweight = 'bold', labelpad = 16)
ax.set_ylabel('Brand Name', fontweight = 'bold')         #^^space between label and axis
plt.grid(True, axis = 'x',linestyle='--', alpha = 0.4)
plt.tight_layout()

#plt.savefig('TOP25_BRANDS.png', transparent = True)
plt.show()
```

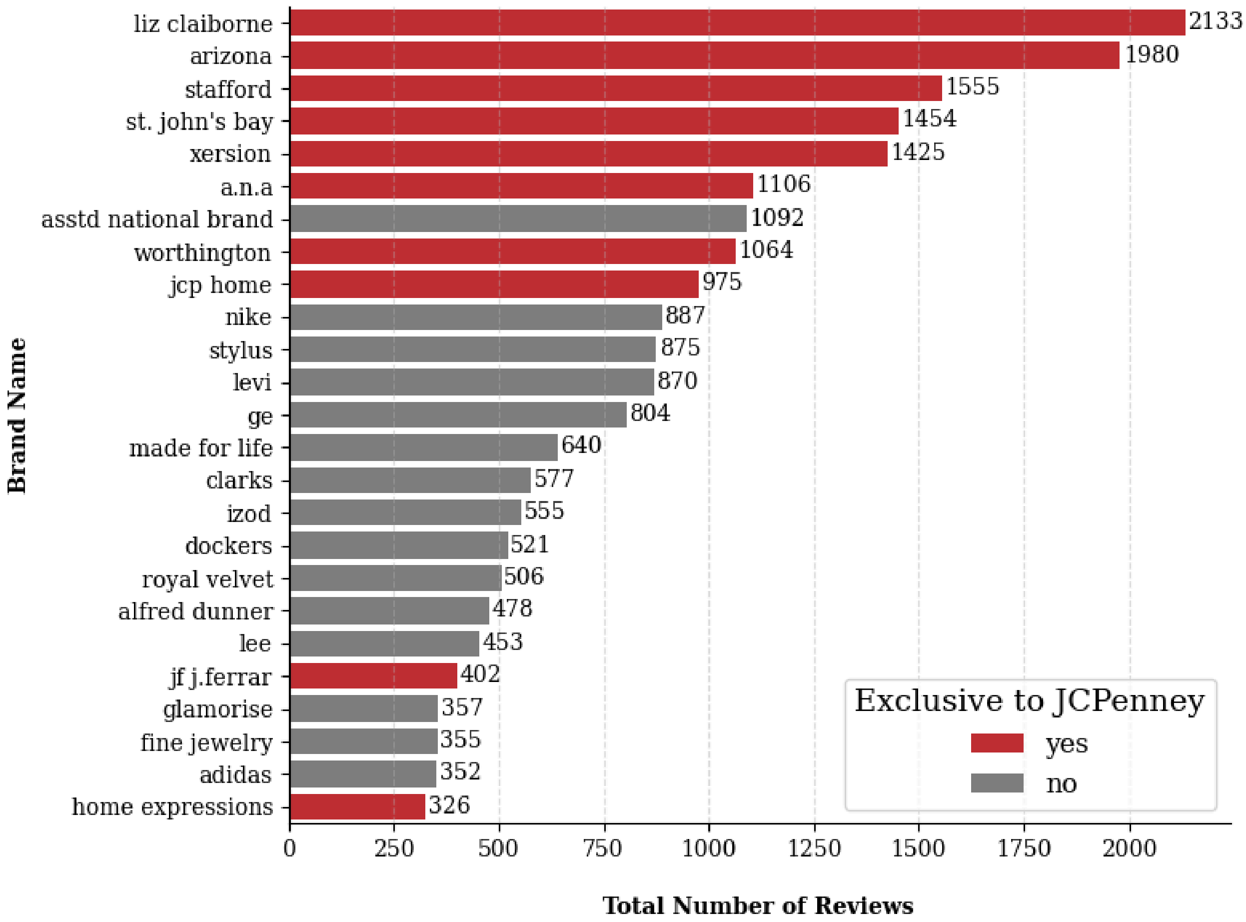


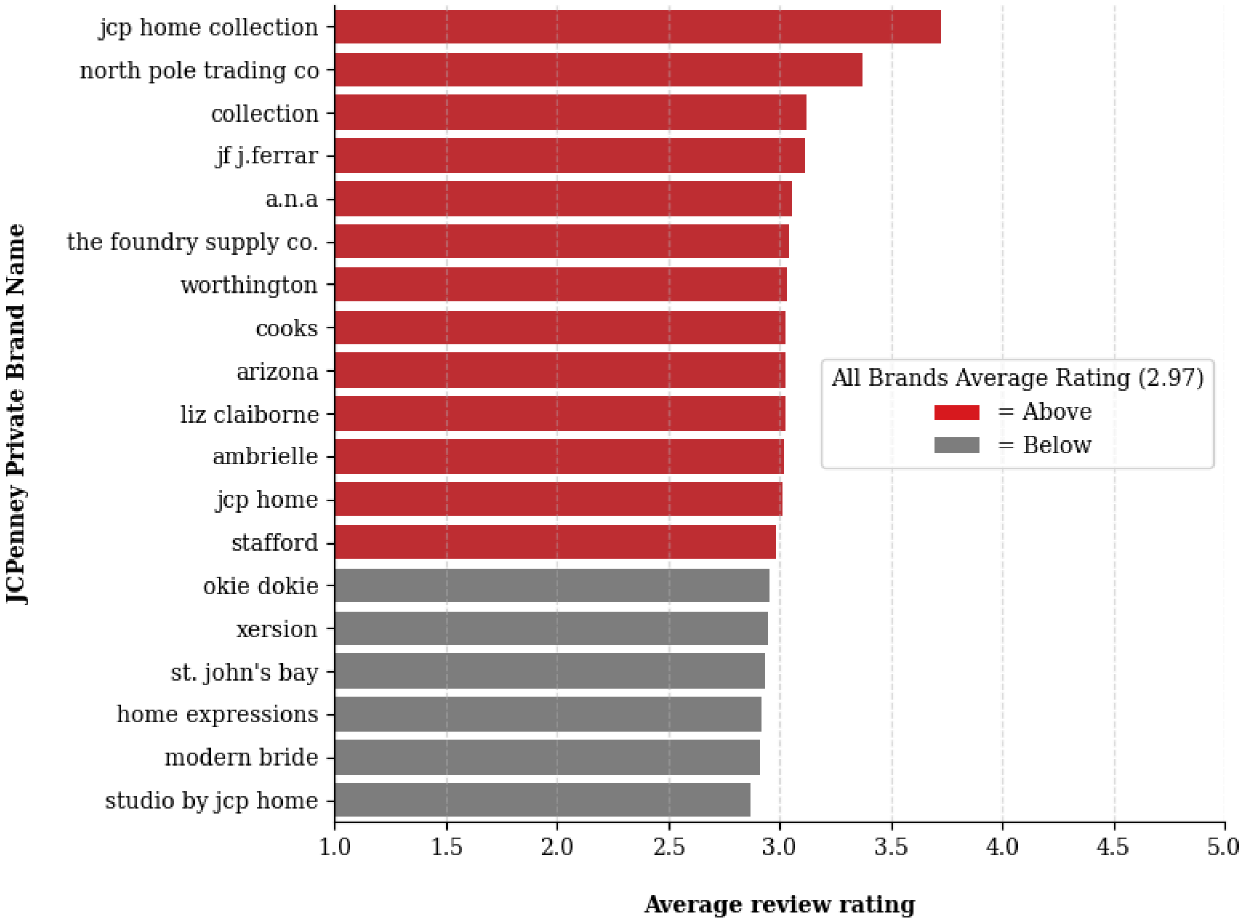
Figure 4

- Average rating of JCPenney Exclusive Brands
- Chose Horizontal barplot to read y-axis brand names easily (rather than Vertical barplot and rotating axis labels), and coloured bars can easily distinguish which brands perform above and below brand rating average

In [38]:
```
#calculate average brand rating for all brands
mean_rating = plot_brand['average_rating'].mean()

#Filter plot_brand by JCPenney exclusives only and sort by
#'average_rating', save as 'top_jcp_brands'
top_jcp_brands = plot_brand[plot_brand['exclusive_to_jcpenney'] == 'yes']
top_jcp_brands = top_jcp_brands.sort_values(by = 'average_rating', ascending = False)
```

In [39]:
```
#Need colour palette for graph, use list comphrension to assign
# if above or below mean rating for all brands
bar_colours = [penney_red if rating > mean_rating else 'grey'
              for rating in top_jcp_brands['average_rating']]

#figure specs
plt.figure(figsize=(8, 6))# ,dpi = 300)

#plotting and coloring graph data
#assign to 'ax' to change figure layout (below)
ax = sns.barplot(
    data=top_jcp_brands,
    x='average_rating',
    y='brand',
    palette= bar_colours)


#Need Patches to indicate color in figure legend
legend_patches = [
    # Patch 1: Above Mean = red
    Patch(facecolor=penney_red, label='= Above'),
    # Patch 2: Below Mean = grey
    Patch(facecolor='grey', label='= Below ')
]
```

```python
#Figure legend
ax.legend(
    handles=legend_patches,
    title='All Brands Average Rating (2.97)',
    loc='center right'
)

#remove right and top axes borders
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

#Axis labels
ax.set_xlabel('Average review rating', fontweight = 'bold', labelpad = 16)
ax.set_xlim(1, 5)
ax.set_ylabel('JCPenney Private Brand Name', fontweight = 'bold',labelpad = 16)

plt.grid(True, axis = 'x',linestyle='--', alpha = 0.4)
plt.tight_layout()
#plt.savefig('JCPenney_AVrating.png', transparent = True)
plt.show()
```



Jcpenney Discount

Let's look at the trends and impact of discounting prpducts, relating back to JCPenney exclusive brands

In [40]:
```python
#Load in jcpenney_products.json
df = jcpenney_dfs['jcpenney_products.json'].copy() #copy() to prevent warnings
#display(df.head(1))

# filter for columns
df = df[['sku','name_title', 'list_price', 'sale_price']]

# convert dtypes of columns
# SKU + Name -> string and list_price + sale_price -> float
df['sku'] = df['sku'].astype('string')
df['name_title'] = df['name_title'].astype('string')
df['list_price'] = pd.to_numeric(df['list_price'], errors = 'coerce')
df['sale_price'] = pd.to_numeric(df['sale_price'], errors = 'coerce')
                                    #^any entry not able to be numeric will be NaN instead
```

```
#show datatypes and no. of non-null values in each column
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7982 entries, 0 to 7981
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   sku         7982 non-null   string 
 1   name_title  7982 non-null   string 
 2   list_price  5816 non-null   float64
 3   sale_price  7719 non-null   float64
dtypes: float64(2), string(2)
memory usage: 249.6 KB
```

Looking at the data, there seems to be alot of NaN values in the `list_price` column, of 7982 entries only 5816 are non-null

We will assume in that case the `sale_price` = `list_price` (i.e. no discount)

In [41]:
```
# fill list_price with sale_price if sale_price is non-null
df['list_price'] = df['list_price'].fillna(df['sale_price'])
```

Cleaning data

- Will remove empty `sku` rows, rows containing `NaN` and rows with `price` < 0.
- Also remove true and 'near' duplicate rows based on sku
  - As some skus have multiple entries but since we lack of timestamped prices **we will simply take the first entry of an sku as it's true price**

In [42]:
```
# check no. rows in df
print(f'Total: {len(df)} rows in df.')

# filter out rows with empty entries for sku
df = df[ df['sku'] != '']
print(f'Remove rows containing empty sku -> {len(df)} rows remaining.')

# filter out rows containing 'NaN'
df.dropna(subset=['sku', 'name_title', 'list_price', 'sale_price'], inplace=True)
print(f'Remove rows containing "NaN" -> {len(df)} rows remaining.')

# filter out negative values (<0) in 'list_price' and 'sale_price' column
df = df[ (df['list_price'] > 0) & (df['sale_price'] > 0) ]
print(f'Remove rows containing negative prices -> {len(df)} rows remain.')

# filter out true and near duplicate rows for same sku
df = df.drop_duplicates(subset = ['sku'])
print(f'Remove rows contain true/near duplicates -> {len(df)} rows remain.')
```

```
Total: 7982 rows in df.
Remove rows containing empty sku -> 7915 rows remaining.
Remove rows containing "NaN" -> 7654 rows remaining.
Remove rows containing negative prices -> 7610 rows remain.
Remove rows contain true/near duplicates -> 5860 rows remain.
```

In [43]:
```
#check each sku is only associated with 1 set of prices
sku_unique = df['sku'].nunique() == len(df)
print(sku_unique)
```

```
True
```

Calculate Discount %

- Calculate %discount between list and sale price.
- Store under new column 'discount_percentage'

In [44]:
```
#1) store numerical difference in column 'discount'
#2) calculate %discount, store in new column
df['discount'] = df['list_price'] - df['sale_price']
df['discount_percentage'] = ((df['discount'] / df['list_price']) * 100).round(2)
```

```
#Save df as df_discount
df_discount = df.copy()
```

Lets merge `df_discount` and `df_brands`

In [45]:
```
#show the df heads and row length
display(df_discount.head(1))
print(f'Rows = {len(df_discount)}')
display(df_brands.head(1))
print(f'Rows = {len(df_brands)}')
```

	sku	name_title	list_price	sale_price	discount	discount_percentage
0	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	41.09	24.16	16.93	41.2

```
Rows = 5860
```

	brand	exclusive_to_jcpenney
sku		
pp5006380337	alfred dunner	no

```
Rows = 6043
```

In [46]:
```
#We want to keep 5860 entries from df_discount, hence we will complete a left join with df_brands
df_discount_brand= pd.merge(df_discount, df_brands, on = 'sku', how='left')
display(df_discount_brand.head(2))
print(f'Rows = {len(df_discount_brand)}')
```

	sku	name_title	list_price	sale_price	discount	discount_percentage	brand	exclusive_to_jcpenney
0	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	41.09	24.16	16.93	41.2	alfred dunner	no
1	pp5006790247	Alfred Dunner® Feels Like Spring 3/4 Sleeve Le...	65.27	39.16	26.11	40.0	alfred dunner	no

```
Rows = 5860
```

`df_discount_brand` contains product price and discount info + exclusivity status

---

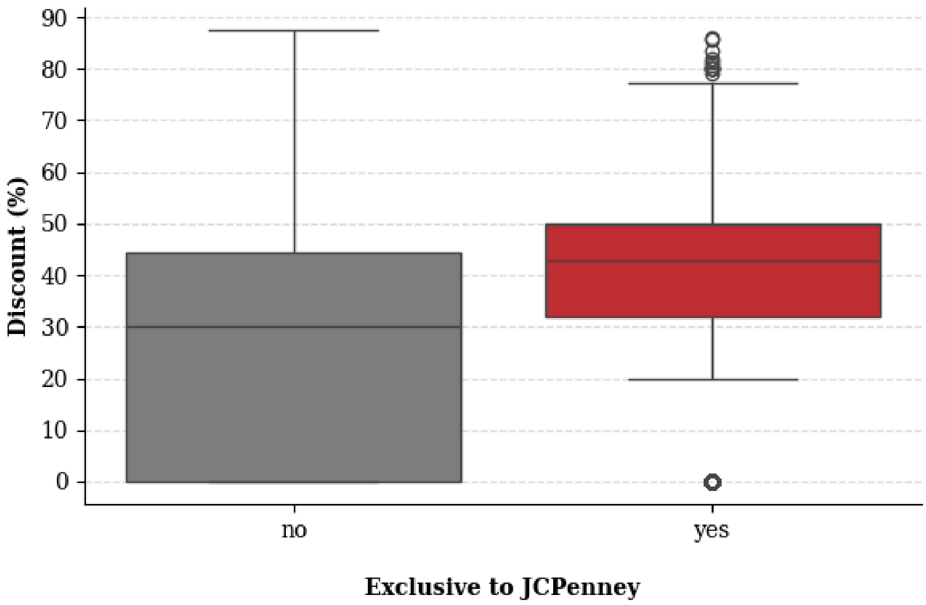
Visualise Discount Impact

Figure 5

- A) Boxplot of Discount %, JCPenney private brand vs other offered brands
- B) Summary table of boxplot statistics (mean, std, min, max etc.)
  - Boxplot is most reasonable visualisation as alternatives like a violin plot lack the easy-to-read demarcation of quartiles that boxplots offer, which will help audiences understanding of data

In [47]:
```
#figure specifications
plt.figure(figsize = (6,4))#, dpi = 300)

#plotting and coloring graph data
#assign to 'ax' to change figure layout (below)
ax = sns.boxplot(
    data=df_discount_brand,
    y='discount_percentage',
    x='exclusive_to_jcpenney',
    #hue = 'exclusive_to_jcpenney',  #color by exclusivity
    palette= ('grey', penney_red)
)

#remove right and top axes borders
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

#set axis labels and grid layout
```

```python
ax.set_xlabel('Exclusive to JCPenney', fontweight = 'bold', labelpad = 16)
ax.set_ylabel('Discount (%)', fontweight = 'bold')
ax.set_yticks([0,10,20,30,40,50,60,70,80,90])
plt.grid(True, axis = 'y' ,linestyle='--', alpha = 0.4)
plt.tight_layout()

#plt.savefig('Discount_boxplot.png', transparent = True)
plt.show()
```



Summary table for figure 5B

To accompany Figure 5A with descriptive stats

In [48]:
```python
#summary table for figure 5B
summary_stats = df_discount_brand.groupby('exclusive_to_jcpenney')['discount_percentage'].describe()
#print(summary_stats)
```

In [49]:
```python
#create a subplot as we need 'ax' for table manipulation
#and 'fig' to finally save figure
fig, ax = plt.subplots(figsize=(6, 1))#, dpi=300)

# remove border when creating axes
ax.axis('off')

#table object
table = ax.table(
    cellText=summary_stats.values.round(1), #take values from summary_stats
    colLabels=summary_stats.columns,     #take column names
    loc='center',              #center table + values in table
    cellLoc='center')

# set table scale and font size
table.set_fontsize(10)
table.scale(1, 1.2)

#Turn table cells transparent for report
#loop through rows
for i in range(len(summary_stats) + 1):
    # Loop through columns
    for j in range(len(summary_stats.columns)):
        cell = table[(i, j)]  #get posiiton in table
        # Set background colour to 'none' (transparent)
        cell.set_facecolor('none')

#plt.savefig('Boxplot table.png' , transparent = True)
plt.show()
```

count	mean	std	min	25%	50%	75%	max
4256.0	27.3	22.0	0.0	0.0	30.0	44.5	87.5
1604.0	38.7	21.7	0.0	31.8	42.9	50.1	86.1

Merging `df_discount` with `df_sku_stats`

- `df_discount` has 5860 entries and `df_sku_stats` has 6043 entries

In [50]:
```
#We want to keep 5860 entries from df_discount, hence we will complete a left join with df_sku_stats
df_discount_sku = pd.merge(df_discount, df_sku_stats, on = 'sku', how='left')
```

In [51]:
```
display(df_discount_sku.head(2))
```

	sku	name_title	list_price	sale_price	discount	discount_percentage	average_product_rating	total_number_review
0	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	41.09	24.16	16.93	41.2	2.979167	4
1	pp5006790247	Alfred Dunner® Feels Like Spring 3/4 Sleeve Le...	65.27	39.16	26.11	40.0	3.750000	

Figure 6

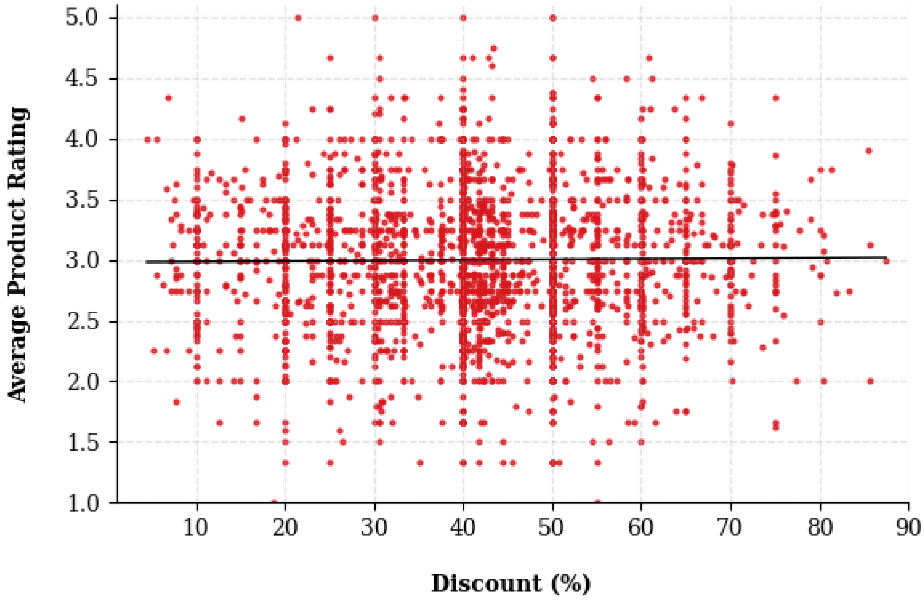
Regression Plot of all products discount % vs. average product rating

- Regression Plot in Seaborn enables the visual aid of the linear regression line on a scatterplot
- Could potentially have used Hexbin plot but as it's not a typical graph used in business reports, therefore elected to use a regression plot which would be more familiar to the JCPenney board

In [52]:
```
#Filter data for when total number review >3 (to prevent skewed results)
# and when discount % is >0 (when there is a discount)
#save df as plot_discount for recall
plot_discount = df_discount_sku[df_discount_sku['total_number_reviews']>=3]
plot_discount = plot_discount[plot_discount['discount_percentage']>=0.1]
```

In [53]:
```
#fig specs
plt.figure(figsize = (6,4))#, dpi = 300)

#plotting data, regplot() will add regression line
ax = sns.regplot(
    data=plot_discount,
    x='discount_percentage',
    y='average_product_rating',
    color = penney_red,
    scatter_kws={'s': 4},
    ci = None,
    line_kws={'color': 'black','linestyle': '-', 'linewidth': 1}
)


#remove right and top axes borders
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)


#plt.title('average product rating vs. discount %')
plt.xlabel('Discount (%)', fontweight = 'bold', labelpad = 15)
ax.set_xlim(1, 90)
plt.ylabel('Average Product Rating', fontweight = 'bold',labelpad = 15)
ax.set_ylim(1, 5.1)
```

```
plt.grid(linestyle = '--', alpha = 0.3)
plt.tight_layout()
#plt.savefig('Scatter_avpr_discount.png', transparent = True)
plt.show()
```



Since we cannot fully trust the visuals, we will employ statistics (linear regression) to determine if there is a linear relationship between variables using pearsons correlation and calculate the p-value.

Null hypothesis: No linear relationship between discount % and average product rating

Alternative hypothesis: linear relation does exist between discount % and average product rating

In [54]:
```
x = plot_discount['discount_percentage']
y = plot_discount['average_product_rating']

# Calculate sample correlation (r) and p-value for figure 6
correlation, p_value = pearsonr(x, y)

print(f"Pearson Correlation (r): {correlation:.3f}")
print(f"P-value: {p_value:.3f}")
```

```
Pearson Correlation (r): 0.012
P-value: 0.526
```

There is no statistically significant relationship between Discount Percentage and Average Product Rating. i.e. P-value > 0.05

The data shows these two factors operate independently of one another. Therefore, we can conclude that the relationship is not real or statistically insignificant.