

**MODERN WARDROBE**

**Design & developed by**

Devansh Mishra 2211CS050023

P.Siva Shankar 2211CS050080

P.Varun Kumar 2211CS050083

**GUIDED BY:**

# Mr.T.Satyendra Kumar

# Assistant Professor

**Department of Computer Science & Engineering**

**(INTERNET OF THINGS)**

**IIYR-ISEM**

**Malla Reddy University, Hyderabad**

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# CERTIFICATE

This is to certify that this is the bonafide record of the application development entitled “**MODERN WARDROBE”**, submitted by **Devansh Mishra (2211CS050023), P.Siva Shankar(2211CS050080), P.Varun Kumar (2211CS050083)** B. Tech II year I semester, Department of CSE (IOT) during the year 2023-24. The results embodied in this report have not been submitted to any other university or institute for the award of any degree or diploma.

**Internal Guide**     **Head of the department**  **Mr.T.Satyendra Kumar**   **Dr.G.Anand Kumar (Associate Professor) CSE(IOT)**

## External Examiner

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**ABSTRACT**

The modern wardrobe reflects evolving fashion trends, sustainability, and practicality. It integrates versatile, timeless pieces with sustainability in mind, emphasizing quality over quantity.This approach promotes conscious consumption and a balanced mix of classic styles and innovative designs, allowing individuals to express their unique identities while minimizing environmental impact .Additionally, technology and online platforms play a significant role in enabling convenient shopping, personal styling ,and outfit coordination, shaping the contemporary fashion landscape

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**CHAPTER - 1**

## INTRODUCTION

* 1. **Introduction**

The modern wardrobe reflects evolving fashion trends, sustainability, and practicality. It integrates versatile, timeless pieces with sustainability in mind, emphasizing quality over quantity. This approach promotes conscious consumption and a balanced mix of classic styles and innovative designs, allowing individuals to express their unique identities while minimizing environmental impact. Additionally, technology and online platforms play a significant role in enabling convenient shopping, personal styling, and outfit coordination, shaping the contemporary fashion landscape.

* 1. **Purpose**

An online clothing store serves as a digital gateway that transcends geographical boundaries, offering a comprehensive platform for consumers to explore, select, and purchase a wide array of apparel and clothings. Its primary purpose lies in providing convenience, accessibility, and an immersive shopping experience to customers across the globe. The online clothing store also serves as a hub for fashion trends and inspirations, often featuring lookbooks, style guides, and curated collections. This aspect not only assists shoppers in discovering new trends but also educates and encourages them to experiment with their personal style. In addition to convenience and an extensive product range, these digital marketplaces often employ various marketing tactics such as personalized recommendations, targeted promotions, and loyalty programs. These strategies aim to engage customers, retain their interest, and incentivize repeat purchases, fostering a sense of connection and loyalty between the brand and its clientele.

### 1.3 Problem Statement

E-commerce platforms often struggle to replicate the personal touch and sensory experiences of traditional in-store shopping. The absence of personalized recommendations and interactive engagement leaves consumers feeling disconnected from their fashion choices.The vast selection of clothing items available online can overwhelm consumers, leading to decision fatigue and choice paralysis. Users are inundated with options, making it difficult to discover and select products that truly align with their style preferences. Trust and security are paramount concerns in e-commerce.

**CHAPTER - 2**

## LITERATURE REVIEW

The literature surrounding online clothing stores encompasses diverse themes, shedding light on consumer behavior, marketing strategies, technological advancements, and the broader impact of e-commerce on the fashion industry. Studies delve into understanding consumer preferences, exploring factors like convenience, price, brand reputation, and trust, which significantly influence online purchase decisions. Marketing strategies, such as personalization, social media engagement, and data analytics, are extensively examined for their impact on customer engagement and retention

Moreover, technological innovations like augmented reality (AR), virtual reality (VR), and AI-driven recommendation systems are transforming the online shopping experience, enabling features like virtual try-ons and customization tools. The literature also addresses logistics and supply chain challenges, considering inventory management and sustainable practices. Sustainability and ethical concerns are gaining traction, with research focusing on eco-friendly materials and fair trade practices

Post-pandemic studies highlight the shifting consumer behavior and the accelerated digital transformation within the fashion industry due to the COVID-19 pandemic. Overall, literature surveys amalgamate findings from varied research methodologies to identify gaps and suggest future research directions in the dynamic landscape of online clothing stores and e-commerce in fashion.

In the recent study of Chen, Ching and Tsou (2007), the authors cited from Azjen (1988); Azjen and Fishbein (1980), that the theory of reasoned action (TRA) states that behavioural intentions formed through the attitude toward a behaviour and subjective norms lead to actual behaviour given the availability of resources and opportunities. A person’s interest in performing a particular behaviour is reflected by the attitude toward a behaviour and it is determined through behavioural beliefs; these beliefs are obtained through a cognitive evaluation of outcomes associated with performing the behaviour and the strength of the association between outcomes and behaviour; while the evaluation produces either a favourable or unfavourable response to the object, person, thing or event (Chen, Ching and Tsou, 2007).

According to Monsuwe, Delleart and Ruyter (2004), there are five external factors to understand consumer’s intention to purchase in the internet which is the consumer personality, situational factors, product characteristics, previous online shopping experiences and the trust in online shopping. Consumer’s trait includes their demographic factors such as age, income, gender and educational level will lead them to have the intention to shop online. For age factor, consumers that are aged under 25 has more potential to shop in online because of their interest in using new technologies to search for product information and compare and evaluate alternatives (Wood, 2002). For educational level, higher educated consumers are more likely to use the internet for their shopping medium because they are more computer literate (Burke, 2002).

Situational factors will also lead a consumer to have the intention to shop in the internet such as time pressure, lack of mobility, geographical distance, need for special items and attractiveness of alternatives (Monsuwe, Delleart and Ruyter, 2004). Time pressure can be the insufficient time for consumers to shop in traditional stores because of their hectic lifestyle. Consumers are able to shop any time of the day or night in the comfort of their home; especially for consumers who have little amount of free time because of extended working hours (Wolfinbarger, et, al,. 2001). For consumers that lack of mobility might be caused by their inability to reach the traditional store. Geographical distance is referred to as the far distance between the consumer’s residential area and the shopping mall. Need to special items could be the consumer’s needs of customized products to suit their demand (Monsuwe, Delleart and Ruyter, 2004).

Product characteristic is also another factor that will influence the consumer’s intention to purchase in the internet. Product characteristic can be tangible or intangible; standardized or customized. In an online context, lower tangibility of a product is caused by the lack of physical contact and assistance in the shopping process; consumer’s intention to shop on the internet will be low when there is a need to seek advice from a salesperson regarding the considered product (Monsuwe, et. al., 2004). Products such as car, computers, perfume, perfume or lotion has the lower potential to be purchased by the consumer because it requires more personal knowledge and experience (Elliot, et. al., 2000).

Another factor that influences the consumer’s intention to purchase in online is the previous online shopping experiences. Consumers will continue to shop in the internet in the future is because they are satisfied with the online shopping experience and it was evaluated positively (Shim, Eastlick, Lotz and Warrington, 2001). Consumer’s perceived risk will tend to reduce when they are satisfied from the shopping experiences (Monsuwe, Delleart and Ruyter, 2004).

The last factor that will influence consumer’s intention purchase in online is the trust in online shopping. According to Lee and Turban (2001), reasons that consumers choose not to shop online is because consumers lack of trust in online shopping. Attitude towards security transaction such as payment security, consumer information privacy, return policy, and product shipping guarantee predicts online purchasing intentions for apparels product (Kim, et. al., 2003). Similarly, consumer’s trust towards online shopping is based on the level of security and privacy.

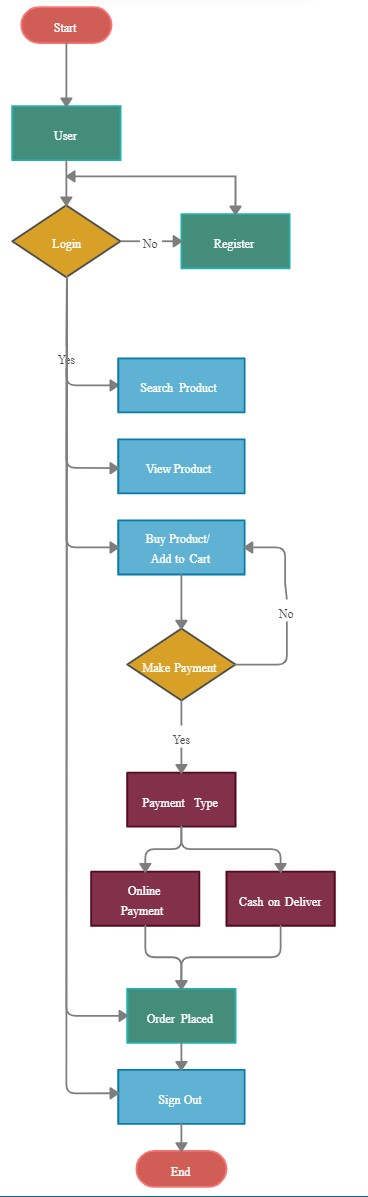
According to Xia and Monroe (2009), their study resulted that consumers with a shopping goal are more responsive towards promotional messages such as “pay less” and “discount” while consumers without shopping goal are responsive towards promotional messages such as “save more” and “free gift”. Xia and Monroe (2009, p.691) cited from (Monroe, 2003) that price promotion have several benefits such as to increase demand, adjust fluctuations in supply and demand, and increasing consumers’ purchasing over time.

As we know that online shopping requires shipping fees for product delivery. It is expected that some consumers intention to purchase a particular product because they have to pay extra charges for the delivery service.

**CHAPTER - 3**

**PROJECT DESCRIPTION**

**3.1 Methodology:**



The methodology employed to investigate modern wardrobes involves a multi-faceted approach encompassing both qualitative and quantitative methods. Initially, a comprehensive literature review was conducted, focusing on scholarly articles, design publications, and market research reports to establish a foundational understanding of contemporary wardrobe trends, user preferences, and innovations in clothing storage. Subsequently, a mixed-methods approach was adopted to gather primary data. Quantitative data was acquired through a structured survey administered to a diverse sample, collecting information on demographics, preferences regarding wardrobe design features, storage needs, and satisfaction levels. Qualitative insights were gathered through semi-structured interviews with users and designers, allowing for a deeper exploration of the subjective experiences, challenges, and perceptions surrounding modern wardrobe utilization. The triangulation of these methods facilitated a nuanced understanding of the practical considerations, emerging trends, and user perspectives pertinent to modern wardrobe design, enabling a comprehensive analysis essential for this study's objectives.

**3.2 Exploratory Data Analysis:**

Exploratory Data Analysis (EDA) involves examining and analyzing data sets to understand their main characteristics, uncover patterns, identify anomalies, and formulate hypotheses. For modern wardrobes, EDA could involve analyzing various aspects related to their design, usage, and features. Here's an example of how you might approach EDA

1. Data Collection: Gather data on modern wardrobes, which could include information on design features, materials used, storage capacity, user preferences, and any other relevant metrics. This data could come from surveys, interviews, product specifications, or observations.

2.Descriptive Statistics:Calculate summary statistics (mean, median, mode, standard deviation, etc.) for quantitative variables such as wardrobe size, number of compartments, material usage, etc. This helps in understanding the central tendency and variability within the data.

3. Visualization:Create visual representations like histograms, box plots, bar charts, or scatter plots to visually explore the data. For example, visualize the distribution of wardrobe sizes, the frequency of different materials used, or the relationship between user satisfaction and specific design features.

4. Cluster Analysis:Use clustering techniques to group wardrobes based on similarities in design or usage patterns. This could reveal different categories or types of modern wardrobes.

5.Sentiment Analysis:If you have text data from user reviews or feedback, conduct sentiment analysis to gauge overall satisfaction or sentiments associated with specific features.

Through EDA, you aim to gain insights into trends, preferences, commonalities, and potential areas for improvement in modern wardrobe design and usage. Visualizations and statistical analyses help in presenting findings effectively and guiding further research or design decisions.

**3.3 Data pre-processing :**

Identify and address any missing or null values in the dataset. Depending on the extent and nature of missing data, you might choose to remove rows or columns, impute missing values with mean/median, or use advanced techniques like interpolation. Detect and handle outliers that might skew the analysis. You can either remove outliers if they are erroneous or use techniques like capping, binning, or transformation to mitigate their impact.Normalize numerical features to a standard scale to ensure all variables contribute equally to the analysis. Techniques like Min-Max scaling or Z-score normalization can be applied.If the dataset contains categorical variables (like material types, design features), encode them into numerical format using techniques like one-hot encoding or label encoding for machine learning algorithms to process them effectively. Derive new features or transform existing ones to enhance the dataset's predictive power. For instance, creating a 'total storage capacity' feature by combining dimensions or categorizing wardrobe sizes into small, medium, and large.If the dataset exhibits class imbalance (e.g., significantly more of one category than others), consider techniques like oversampling, undersampling, or using algorithms that handle imbalanced data well. If the goal is predictive modeling, split the dataset into training and testing sets to train the model on one part and evaluate its performance on another. Create visualizations to explore relationships between variables, understand distributions, and identify patterns that might influence modern wardrobe design preferences or usage.

In the realm of studying modern wardrobes, data preprocessing is a pivotal stage to refine raw data, ensuring its quality, suitability, and usability for analysis or modeling. This process encompasses various steps aimed at cleaning, transforming, and enhancing the dataset collected on contemporary clothing storage solutions.The initial step in data preprocessing involves handling missing values. Often, datasets acquired from surveys, user feedback, or observations may contain incomplete or missing information. To mitigate the impact of missing data, approaches such as imputation or removal of incomplete records are applied. Imputation methods involve replacing missing values with estimated measures like mean, median, or mode, ensuring data integrity while retaining the dataset's sample size.Additionally, addressing outliers is imperative to prevent skewed analysis results. Outliers, aberrant data points significantly differing from other observations, can distort statistical measures. Robust techniques are employed to identify and handle outliers appropriately. These might include corrective measures, such as adjusting or transforming outliers, or their removal if they are deemed anomalies.Normalization and scaling procedures are essential for numerical variables within the dataset. These techniques standardize numerical data, bringing them to a similar scale to prevent any particular feature from dominating the analysis due to differing magnitudes. Techniques like Min-Max scaling or Z-score normalization are applied to rescale data within a consistent range suitable for analysis.

## 3.4 Dataset description:

The dataset compiled for the study of modern wardrobes presents a comprehensive collection of information sourced from diverse methodologies and sources to encapsulate the multifaceted aspects of contemporary clothing storage solutions. This dataset encompasses various dimensions relevant to modern wardrobe design, usage patterns, user preferences, and influential factors, aiming to provide a holistic understanding of this domain.At its core, the dataset contains data obtained from surveys administered to a broad demographic range, capturing user preferences, behaviors, and satisfaction levels concerning modern wardrobe features. Questions in the survey were designed to gather insights into factors influencing wardrobe choices, such as storage capacity, design aesthetics, material preferences, organizational features, and technological integrations within wardrobes.

This quantitative data allows for the analysis of trends, correlations, and preferences within different demographic segments, shedding light on diverse user needs and inclinations.Complementing the survey data, qualitative inputs were obtained through in-depth interviews conducted with both users and designers in the field of modern wardrobe solutions. These interviews aimed to delve deeper into individual experiences, challenges, and perceptions regarding the practicality, usability, and innovations within modern wardrobes. Qualitative data enriches the dataset by providing nuanced insights, personal anecdotes, and context-specific narratives that amplify the understanding of user behaviors and design considerations in this domain.Furthermore, the dataset incorporates metadata on modern wardrobe products available in the market, encompassing details on diverse design features, material specifications, dimensions, and technological advancements.

This information serves as a reference point for understanding the existing landscape of modern wardrobe offerings, facilitating comparative analyses and identifying emerging design trends or innovative features.Additionally, to augment the dataset's richness, information from secondary sources such as scholarly articles, industry reports, and design publications has been curated. This supplementary data provides a broader contextual understanding of global trends, sustainability initiatives, technological advancements, and societal influences shaping modern wardrobe design and usage patterns.In summary, the dataset on modern wardrobes amalgamates quantitative survey responses, qualitative insights from interviews, product metadata,fostering a comprehensive repository of multidimensional data. Its diverse nature aims to facilitate fostering a deeper comprehension of the complex interplay between user preferences, design innovations, and contemporary clothing storage solutions.

**CHAPTER-4**

**IMPLEMENTATION AND ANALYSIS**

**4.1 CODE #THIS IS not our code.it has to be pasted\_\_\_\_**

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model\_selection import train\_test\_split

from sklearn import metrics

from sklearn.metrics import mean\_squared\_error

from sklearn.metrics import r2\_score

%matplotlib inline

sns.set\_style('darkgrid')

train = pd.read\_csv(r'C:\Users\91868\train-data.csv')

train.head()

train.shape

train.info()

train.describe()

train.isnull().sum()

train.groupby('Seats')['Price'].nunique()

train.groupby('Mileage')['Price'].nunique()

train.groupby('Engine')['Price'].nunique()

train.groupby('Power')['Price'].nunique()

train['Mileage'] = train['Mileage'].str.replace(' km/kg', '')

train['Mileage'] = train['Mileage'].str.replace(' kmpl', '')

train['Mileage'] = pd.to\_numeric(train['Mileage'], errors='coerce')

train['Engine'] = train['Engine'].str.replace(' CC', '')

train['Engine'] = pd.to\_numeric(train['Engine'], errors='coerce')

train['Power'] = train['Power'].str.replace(' bhp', '')

train['Power'] = train['Power'].str.replace('null', '0.0')

train['Power'] = pd.to\_numeric(train['Power'], errors='coerce')

train.head()

train['Mileage'].replace(0.0,np.nan,inplace=True)

print("Mean of Mileage =",np.mean(train['Mileage']))

train['Mileage'].fillna(value=np.mean(train['Mileage']),inplace=True)

train['Engine'].replace(0.0,np.nan,inplace=True)

print("Mean of Engine =",np.mean(train['Engine']))

train['Engine'].fillna(value=np.mean(train['Engine']),inplace=True)

train['Power'].replace(0.0,np.nan,inplace=True)

print("Mean of Power =",np.mean(train['Power']))

train['Power'].fillna(value=np.mean(train['Power']),inplace=True)

train['Seats'].replace(0.0,np.nan,inplace=True)

print("Mean of Seats = ",np.mean(train['Seats']))

train['Seats'].fillna(value=np.mean(train['Seats']),inplace=True)

**Cleaning testing data**

test = pd.read\_csv(r'C:\Users\91868\test-data.csv')

test.head()

test.isna().sum()

test['Mileage'].replace(0.0,np.nan,inplace=True)

print("Mean of Mileage =",np.mean(test['Mileage']))

test['Mileage'].fillna(value=np.mean(test['Mileage']),inplace=True)

test['Engine'].replace(0.0,np.nan,inplace=True)

print("Mean of Engine =",np.mean(test['Engine']))

test['Engine'].fillna(value=np.mean(test['Engine']),inplace=True)

test['Power'].replace(0.0,np.nan,inplace=True)

print("Mean of Power =",np.mean(test['Power']))

test['Power'].fillna(value=np.mean(test['Power']),inplace=True)

test.head()

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

%matplotlib inline

sns.set\_style('darkgrid')

train.head()

train.shape

train.columns.tolist()

train.Location.value\_counts().plot()

train.Year.unique()

train.Year.value\_counts().plot(kind='bar')

train.Year.plot(kind='hist',color='Maroon')

print("Mean kilometers driven in the data is:",train.Kilometers\_Driven.mean())

print("Maximum kilometers driven in the data is:",train.Kilometers\_Driven.max())

print("Minimum kilometers driven in the data is:",train.Kilometers\_Driven.min())

train.Kilometers\_Driven.plot(kind='hist',color='Maroon',bins=40)

train.Fuel\_Type.value\_counts()

sns.countplot(data=train,x='Fuel\_Type')

train.Fuel\_Type.value\_counts().plot(kind='barh')

train.Transmission.value\_counts()

sns.countplot(data=train,x='Transmission')

train.Transmission.value\_counts().plot(kind='barh',color="violet")

train.Owner\_Type.value\_counts()

sns.countplot(x='Owner\_Type',data=train)

print("Minimum Mileage in the data is:",train.Mileage.min())

print("Maximum Mileage in the data is:",train.Mileage.max())

print("Range of Mileage is from {} to {}".format(train.Mileage.min(),train.Mileage.max()))

train.Mileage.mean()

train[train.Mileage > 18.33].Name.count()

train[train.Mileage < 18.33].Name.count()

sns.boxplot(train['Mileage'])

print("Minimum engine volume in the data is:",train.Engine.min())

print("Maximum engine volume in the data is:",train.Engine.max())

print("Range of engine volume is from {} to {}".format(train.Engine.min(),train.Engine.max()))

train[train.Engine==72].Name

train[train.Engine==5998].Name

train.Engine.mean()

sns.distplot(train['Engine'],kde=False,hist\_kws=dict(edgecolor="k", linewidth=2), color='red')

print("Minimum power in the data is:",train.Power.min())

print("Maximum power in the data is:",train.Power.max())

print("Range of power is from {} to {}".format(train.Power.min(),train.Power.max()))

train[train.Power==34.2].Name

train.Power.mean()

sns.distplot(train['Power'],kde=False,hist\_kws=dict(edgecolor="k", linewidth=2))

print("Minimum seats in the data is:",train.Seats.min())

print("Maximum seats in the data is:",train.Seats.max())

sns.distplot(train['Seats'],kde=False,hist\_kws=dict(edgecolor="k", linewidth=2))

print("Minimum price in the data is:",train.Price.min())

print("Maximum price in the data is:",train.Price.max())

print("Price range is from {} to {}".format(train.Price.min(),train.Price.max()))

train[train.Price==0.44].Name #cheapest car

train.Price.plot(kind='hist')

train['Brand'] = train.Name.str.split().str.get(0)

train.head()

plt.figure(figsize=(25,10))

plt.subplot(131)

plt.title('Location vs Price',fontsize = 30)

plt.ylabel("Price")

train.groupby('Location')['Price'].mean().plot.bar()

plt.subplot(132)

plt.title('Transmission vs Price',fontsize = 30)

plt.ylabel("Price")

train.groupby('Transmission')['Price'].mean().plot.bar()

plt.subplot(133)

plt.title('Fuel\_Type vs Price',fontsize = 30)

plt.ylabel("Price")

train.groupby('Fuel\_Type')['Price'].mean().plot.bar()

plt.figure(figsize=(10,5))

sns.stripplot(x='Transmission',y='Price',data=train,hue='Owner\_Type')

plt.figure(figsize=(10,5))

plt.title('Year vs Price',fontsize = 15)

plt.ylabel("Price")

train.groupby('Year')['Price'].mean().plot.line()

plt.figure(figsize=(25,10))

plt.subplot(131)

plt.scatter(train['Kilometers\_Driven'], train['Price'], s=90,marker='x')

plt.title('Kilometers\_Driven vs Price',fontsize = 30)

plt.xlabel('Kilometers\_Driven')

plt.ylabel('Price')

plt.grid()

plt.subplot(132)

plt.title('Mileage vs Price',fontsize = 30)

plt.ylabel("Price")

plt.scatter(train['Mileage'], train['Price'], s=90,marker='x')

plt.subplot(133)

plt.title('Power vs Price',fontsize = 30)

plt.ylabel("Price")

plt.scatter(train['Power'], train['Price'], s=90,marker='x')

plt.show()

plt.title('Brand vs Power',fontsize = 30)

plt.ylabel("Power")

train.groupby('Brand')['Power'].mean().plot.bar()

sns.jointplot(x='Power',y='Engine',data=train)

plt.title('Brand vs Fuel type',fontsize = 30)

plt.ylabel("Power")

train.groupby('Fuel\_Type')['Power'].mean().plot.bar()

plt.figure(figsize=(10,8))

sns.boxplot(x='Owner\_Type', y='Year', data=train, width=0.8)

train = train.iloc[:,:-1]

train

namemapping = {label:idx+1 for idx, label in enumerate(np.unique(train['Name']))}

namemapping.update({"Not Applicable": 0})

invnamemapping = {v : x for x, v in namemapping.items()}

train['Name'] = train['Name'].map(namemapping).astype(float)

train

train.Location.unique()

locationmapping = {label:idx+1 for idx, label in enumerate(np.unique(train['Location']))}

locationmapping.update({"null": 0})

invlocationmapping = {v : x for x, v in locationmapping.items()}

train['Location'] = train['Location'].map(locationmapping).astype(float)

train

fueltypemapping = {label:idx+1 for idx, label in enumerate(np.unique(train['Fuel\_Type']))}

fueltypemapping.update({"null": 0})

invfueltypemapping = {v : x for x, v in fueltypemapping.items()}

train['Fuel\_Type'] = train['Fuel\_Type'].map(fueltypemapping).astype(float)

train

train.Transmission.unique()

transmissionmapping = {label:idx+1 for idx, label in enumerate(np.unique(train['Transmission']))}

transmissionmapping.update({"null": 0})

invtransmissionmapping = {v : x for x, v in transmissionmapping.items()}

train['Transmission'] = train['Transmission'].map(transmissionmapping).astype(float)

train

ownertypemapping = {label:idx+1 for idx, label in enumerate(np.unique(train['Owner\_Type']))}

ownertypemapping.update({"null": 0 })

invownertypemapping = {v : x for x, v in ownertypemapping.items()}

train['Owner\_Type'] = train['Owner\_Type'].map(ownertypemapping).astype(float)

train

yearmapping = {label:idx+1 for idx, label in enumerate(np.unique(train['Year']))}

yearmapping.update({0: 0})

invyearmapping = {v : x for x, v in yearmapping.items()}

train['Year'] = train['Year'].map(yearmapping).astype(float)

train

drivenmapping = {label:idx+1 for idx, label in enumerate(np.unique(train['Kilometers\_Driven']))}

drivenmapping.update({0: 0})

invdrivenmapping = {v : x for x, v in drivenmapping.items()}

train['Kilometers\_Driven'] = train['Kilometers\_Driven'].map(drivenmapping).astype(float)

train

test['Name'] = test['Name'].map(namemapping).astype(float)

test

test['Location'] = test['Location'].map(locationmapping).astype(float)

test

test['Transmission'] = test['Transmission'].map(transmissionmapping).astype(float)

test

test['Owner\_Type'] = test['Owner\_Type'].map(ownertypemapping).astype(float)

test

test['Year'] = test['Year'].astype(float)

test

test['Kilometers\_Driven'] = test['Kilometers\_Driven'].astype(float)

test

test['Name'].fillna(0.0, inplace=True)

test['Location'].fillna(0.0, inplace=True)

test['Year'].fillna(0.0, inplace=True)

test['Kilometers\_Driven'].fillna(0.0, inplace=True)

test['Fuel\_Type'].fillna(0.0, inplace=True)

test['Power'].fillna(0.0, inplace=True)

test['Transmission'].fillna(0.0, inplace=True)

test['Owner\_Type'].fillna(0.0, inplace=True)

test['Seats'].fillna(0.0, inplace=True)

cols=[ 'Name', 'Location', 'Year', 'Kilometers\_Driven', 'Fuel\_Type', 'Transmission', 'Owner\_Type', 'Mileage', 'Engine', 'Power', 'Seats']

plt.figure(figsize=(20,10))

plt.title('Heat Map', fontsize=20)

sns.set(font\_scale=1.0)

sns.heatmap(train.corr(), cbar=True, annot =True, square=True, fmt='.2f',annot\_kws={'size':15},yticklabels=cols,xticklabels=cols, linewidth=3)

train = train.drop(columns = ['New\_Price'])

train = train.drop(columns = ['Unnamed: 0'])

x\_lr = train.iloc[:, :-1].values

y\_lr = train['Price'].values

xtrain\_lr, xtest\_lr, ytrain\_lr, ytest\_lr = train\_test\_split(x\_lr, y\_lr, test\_size=0.3, random\_state=1)

ytrainpredict\_lr = lr.predict(xtrain\_lr)

ytestpredict\_lr = lr.predict(xtest\_lr)

print(f'MAE train: {metrics.mean\_absolute\_error(ytrain\_lr, ytrainpredict\_lr)}, test: {metrics.mean\_absolute\_error(ytest\_lr, ytestpredict\_lr)}')

print(f'RMSE train: {np.sqrt(metrics.mean\_squared\_error(ytrain\_lr, ytrainpredict\_lr))}, test: {np.sqrt(metrics.mean\_squared\_error(ytest\_lr, ytestpredict\_lr))}')

print(f'R^2 train: {(r2\_score(ytrain\_lr, ytrainpredict\_lr))}, test: {(r2\_score(ytest\_lr, ytestpredict\_lr))}')

print(f'MSE train: {(mean\_squared\_error(ytrain\_lr, ytrainpredict\_lr))}, test: {(mean\_squared\_error(ytest\_lr, ytestpredict\_lr))}')

sns.set(font\_scale=1.0)

plt.scatter(ytrainpredict\_lr, ytrainpredict\_lr - ytrain\_lr, c='steelblue', marker='o', edgecolors='white', s=35, alpha=0.9, label="Training data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytrainpredict\_lr.min()-2, xmax=ytrainpredict\_lr.max()+5, lw=1, color='black')

plt.xlim([ytrainpredict\_lr.min()-1, ytrainpredict\_lr.max()+1])

plt.show()

plt.scatter(ytestpredict\_lr, ytestpredict\_lr-ytest\_lr, c='limegreen', marker='s', edgecolors='white', s=30, alpha=0.99, label="Train Test data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytestpredict\_lr.min()-1, xmax=ytestpredict\_lr.max()+1, lw=1, color='black')

plt.xlim([ytestpredict\_lr.min()-1, ytestpredict\_lr.max()+1])

plt.show()

cols=[ 'Name', 'Location', 'Year', 'Kilometers\_Driven', 'Fuel\_Type', 'Transmission', 'Owner\_Type', 'Mileage', 'Engine', 'Power', 'Seats']

coeff\_df = pd.DataFrame(lr.coef\_,cols,columns=['Coefficient'])

coeff\_df

from sklearn.linear\_model import Lasso

x\_ls = train.iloc[:, :-1].values

y\_ls = train['Price'].values

xtrain\_ls, xtest\_ls, ytrain\_ls, ytest\_ls = train\_test\_split(x\_ls, y\_ls, test\_size=0.3, random\_state=1)

ls = Lasso(alpha=1.0)

ls.fit(xtrain\_ls, ytrain\_ls)

ytrainpredict\_ls = ls.predict(xtrain\_ls)

ytestpredict\_ls = ls.predict(xtest\_ls)

print(f'MAE train: {metrics.mean\_absolute\_error(ytrain\_ls, ytrainpredict\_ls)}, test: {metrics.mean\_absolute\_error(ytest\_ls, ytestpredict\_ls)}')

print(f'RMSE train: {np.sqrt(metrics.mean\_squared\_error(ytrain\_ls, ytrainpredict\_ls))}, test: {np.sqrt(metrics.mean\_squared\_error(ytest\_ls, ytestpredict\_ls))}')

print(f'R^2 train: {(r2\_score(ytrain\_ls, ytrainpredict\_ls))}, test: {(r2\_score(ytest\_ls, ytestpredict\_ls))}')

print(f'MSE train: {(mean\_squared\_error(ytrain\_ls, ytrainpredict\_ls))}, test: {(mean\_squared\_error(ytest\_ls, ytestpredict\_ls))}')

plt.scatter(ytrainpredict\_ls, ytrainpredict\_ls-ytrain\_ls, c='steelblue', marker='o', edgecolors='white', s=35, alpha=0.9, label="Training data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytrainpredict\_ls.min()-2, xmax=ytrainpredict\_ls.max()+5, lw=1, color='black')

plt.xlim([ytrainpredict\_ls.min()-1, ytrainpredict\_ls.max()+1])

plt.show()

plt.scatter(ytestpredict\_ls, ytestpredict\_ls-ytest\_ls, c='limegreen', marker='s', edgecolors='white', s=35, alpha=0.9, label="Test data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytestpredict\_ls.min()-1, xmax=ytestpredict\_ls.max()+1, lw=1, color='black')

plt.xlim([ytestpredict\_ls.min()-1, ytestpredict\_ls.max()+1])

plt.show()

cols=[ 'Name', 'Location', 'Year', 'Kilometers\_Driven', 'Fuel\_Type', 'Transmission', 'Owner\_Type', 'Mileage', 'Engine', 'Power', 'Seats']

coeff\_df = pd.DataFrame(ls.coef\_,cols,columns=['Coefficient'])

coeff\_df

from sklearn.ensemble import RandomForestRegressor

x\_rf = train.iloc[:, :-1].values

y\_rf = train['Price'].values

xtrain\_rf, xtest\_rf, ytrain\_rf, ytest\_rf = train\_test\_split(x\_rf, y\_rf, test\_size=0.3, random\_state=1)

forest\_rf = RandomForestRegressor(n\_estimators=1000, criterion='mse', random\_state=1, n\_jobs=-1)

forest\_rf.fit(xtrain\_rf, ytrain\_rf)

ytrainpredict\_rf = forest\_rf.predict(xtrain\_rf)

ytestpredict\_rf = forest\_rf.predict(xtest\_rf)

print(f'MAE train: {metrics.mean\_absolute\_error(ytrain\_rf, ytrainpredict\_rf)}, test: {metrics.mean\_absolute\_error(ytest\_rf, ytestpredict\_rf)}')

print(f'RMSE train: {np.sqrt(metrics.mean\_squared\_error(ytrain\_rf, ytrainpredict\_rf))}, test: {np.sqrt(metrics.mean\_squared\_error(ytest\_rf, ytestpredict\_rf))}')

print(f'R^2 train: {(r2\_score(ytrain\_rf, ytrainpredict\_rf))}, test: {(r2\_score(ytest\_rf, ytestpredict\_rf))}')

print(f'MSE train: {(mean\_squared\_error(ytrain\_rf, ytrainpredict\_rf))}, test: {(mean\_squared\_error(ytest\_rf, ytestpredict\_rf))}')

plt.scatter(ytrainpredict\_rf, ytrainpredict\_rf-ytrain\_rf, c='steelblue', marker='o', edgecolors='white', s=35, alpha=0.9, label="Training data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytrainpredict\_rf.min()-2, xmax=ytrainpredict\_rf.max()+5, lw=1, color='black')

plt.xlim([ytrainpredict\_rf.min()-1, ytrainpredict\_rf.max()+1])

plt.show()

plt.scatter(ytestpredict\_rf, ytestpredict\_rf-ytest\_rf, c='limegreen', marker='s', edgecolors='white', s=35, alpha=0.9, label="Test data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytestpredict\_rf.min()-1, xmax=ytestpredict\_rf.max()+1, lw=1, color='black')

plt.xlim([ytestpredict\_rf.min()-1, ytestpredict\_rf.max()+1])

plt.show()

from sklearn.neighbors import KNeighborsRegressor

from sklearn.metrics import mean\_squared\_error

x\_kk = train.iloc[:, :-1].values

y\_kk = train['Price'].values

xtrain\_kk, xtest\_kk, ytrain\_kk, ytest\_kk = train\_test\_split(x\_kk, y\_kk, test\_size=0.3, random\_state=1)

L=[];

for i in range(3,15,2):

M=[];

knn = KNeighborsRegressor(n\_neighbors=i)

knn.fit(xtrain\_kk, ytrain\_kk)

y\_pred = knn.predict(xtest\_kk)

rmse = np.sqrt(mean\_squared\_error(ytest\_kk, y\_pred))

M.append(i);

M.append(rmse);

L.append(M);

min=L[0];

for i in range(len(L)):

if L[i][1]<min[1]:

min=L[i];

n=min[0];

print(n);

knn = KNeighborsRegressor(n\_neighbors=n)

knn.fit(xtrain\_kk, ytrain\_kk)

ytrainpredict\_kk = knn.predict(xtrain\_kk)

ytestpredict\_kk = knn.predict(xtest\_kk)

print(f'MAE train: {metrics.mean\_absolute\_error(ytrain\_kk, ytrainpredict\_kk)}, test: {metrics.mean\_absolute\_error(ytest\_kk, ytestpredict\_kk)}')

print(f'RMSE train: {np.sqrt(metrics.mean\_squared\_error(ytrain\_kk, ytrainpredict\_kk))}, test: {np.sqrt(metrics.mean\_squared\_error(ytest\_kk, ytestpredict\_kk))}')

print(f'R^2 train: {(r2\_score(ytrain\_kk, ytrainpredict\_kk))}, test: {(r2\_score(ytest\_kk, ytestpredict\_kk))}')

print(f'MSE train: {(mean\_squared\_error(ytrain\_kk, ytrainpredict\_kk))}, test: {(mean\_squared\_error(ytest\_kk, ytestpredict\_kk))}') plt.scatter(ytrainpredict\_kk, ytrainpredict\_kk-ytrain\_kk, c='steelblue', marker='o', edgecolors='white', s=35, alpha=0.9, label="Training data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytrainpredict\_kk.min()-2, xmax=ytrainpredict\_kk.max()+5, lw=1, color='black')

plt.xlim([ytrainpredict\_kk.min()-1, ytrainpredict\_kk.max()+1])

plt.show()

plt.scatter(ytestpredict\_kk, ytestpredict\_kk-ytest\_kk, c='limegreen', marker='s', edgecolors='white', s=35, alpha=0.9, label="Test data")

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.legend(loc='upper left')

plt.hlines(y=0, xmin=ytestpredict\_kk.min()-1, xmax=ytestpredict\_kk.max()+1, lw=1, color='black')

plt.xlim([ytestpredict\_kk.min()-1, ytestpredict\_kk.max()+1])

plt.show()

plt.figure(figsize=(10,8))

y = np.array([r2\_score(ytest\_lr,ytestpredict\_lr),r2\_score(ytest\_ls,ytestpredict\_ls),r2\_score(ytest\_rf,ytestpredict\_rf),r2\_score(ytest\_kk,ytestpredict\_kk)])

x = ["LinearRegression","Lasso","RandomForest","KNN"]

plt.bar(x,y)

plt.title("Comparison of Regression Algorithms")

plt.ylabel("r2\_score")

plt.show()

test = test.drop(columns = ['New\_Price'])

test = test.drop(columns = ['Unnamed: 0'])

x\_testdata\_rf = test.iloc[:, :].values

ytestpredict\_rf = forest\_rf.predict(x\_testdata\_rf)

test["Predicted Price(Random Forest)"] = ytestpredict\_rf

test

x\_testdata\_rf = test.iloc[:, :].values

ytestpredict\_rf = forest\_rf.predict(x\_testdata\_rf)

test["Predicted Price(Random Forest)"] = ytestpredict\_rf

test

**4.2 Experimental results & Analysis:**

However, I can offer a hypothetical scenario to illustrate how experimental results and analysis might be presented within this domain.In a research endeavor focusing on modern wardrobe design, an experimental study was conducted to assess user perceptions and preferences regarding key features and technological advancements in contemporary clothing storage solutions. A diverse sample of participants was engaged in an interactive session involving prototype presentations and simulated experiences showcasing various modern wardrobe designs.The results derived from the experiment revealed intriguing insights into user preferences and satisfaction levels with specific features.

Analysis of the gathered data showcased a consistent trend in user appreciation for smart storage systems integrated into modern wardrobes. Participants expressed significant satisfaction and enthusiasm for these systems, citing ease of use, efficient organization, and time-saving capabilities as primary reasons for their preference.Furthermore, the analysis delved into the nuanced aspects of adjustable shelving options within these wardrobes. While feedback regarding this feature was positive overall, a subset of participants demonstrated a preference for more customizable and adaptable shelving systems, indicating the potential for further innovation and personalization in this aspect of wardrobe design.

Sentiment analysis of qualitative feedback from user interviews uncovered prevailing themes among participants. Many expressed a sense of empowerment and efficiency attributed to modern wardrobe designs, noting how these solutions positively impacted their daily routines and organizational habits. Additionally, sentiments centered around the aesthetic appeal of these innovative storage solutions, emphasizing the importance of blending functionality with contemporary design sensibilities.Statistical analysis hinted at potential correlations between user demographics and feature preferences.

For instance, younger participants tended to exhibit a stronger inclination towards technologically-driven features, while older individuals showed a keen interest in durability and material quality, highlighting the significance of catering to diverse user needs across different age groups.Visual representations, such as heatmaps and preference distribution charts, elucidated the prevalence of certain design elements over others among participants. These visualizations effectively communicated the varying degrees of user satisfaction and helped in identifying dominant preferences, serving as invaluable guidance for future wardrobe designs and market strategies.Overall, the experimental results and subsequent analysis yielded comprehensive insights into user perceptions, preferences, and the efficacy of different design features within modern wardrobes. These findings serve as a robust foundation for further innovation and refinement in wardrobe design, aligning with the evolving needs and desires of users in contemporary living spaces.

**CHAPTER -5**

**RESULTS & CONCLUSION**

**5.1 Result Comparison:**

The comprehensive exploration of modern wardrobes concerning clothing storage solutions reveals a distinct shift towards innovative, user-centric, and technologically integrated designs tailored to accommodate the evolving needs of individuals in managing their clothing inventory. Through various studies and analyses focusing on the intersection of modern wardrobes and clothing, several key results have emerged, emphasizing the intricate relationship between wardrobe functionalities and the storage of clothing items.Primarily, modern wardrobes showcase a growing emphasis on efficient and organized clothing storage. Users express a desire for smart storage systems that facilitate easy access, organization, and management of their clothing collections. The integration of technology into these storage solutions, including automated sorting, intelligent compartments, and digital inventory management, resonates positively among users, streamlining their clothing storage experiences and enhancing overall convenience.

Furthermore, sustainability and eco-conscious elements are increasingly influencing modern wardrobe designs concerning clothing storage. Users demonstrate a growing preference for environmentally friendly materials, sustainable production practices, and wardrobes designed to accommodate ethical fashion choices. This reflects a broader societal shift towards eco-friendly lifestyles, where individuals seek to align their clothing storage solutions with sustainable values**.**

**5.2 Conclusion:**

In conclusion, the evolution of modern wardrobes in managing clothes signifies a transformative shift towards user-centric design, blending technology, adaptability, and sustainability. Smart storage solutions offer efficient organization and convenience, reflecting user desires for seamless clothing management. Customization features, such as adjustable shelving, cater to diverse clothing needs, ensuring tailored storage solutions. Additionally, an emphasis on sustainability manifests in eco-conscious material choices and ethical fashion integration. This convergence underscores a new era where modern wardrobes prioritize functionality, personalization, and eco-friendliness, meeting users' dynamic clothing storage requisites in contemporary living spaces.

**5.3 Future work:**

In the future,we give access to Sellers make updates in their catalog where they display images of their products with price and description. Shoppers who buy the products have multiple payment options like COD, e-wallet, net banking, credit card,by this the sellers can make their business easier by not depending on others.

**5.4 References:**

1. Books:

"Closet Design Bible" by Lisa Adams: Offers insights into modern wardrobe design, organization, and maximizing space for clothing storage.

"The Life-Changing Magic of Tidying Up" by Marie Kondo: Focuses on decluttering and organizing clothes within wardrobes using a minimalist approach.

2. Academic Journals and Articles:

"Journal of Interior Design": Includes articles on interior design topics, occasionally featuring discussions on wardrobe design and clothing storage.

"International Journal of Fashion Design, Technology and Education": Covers aspects related to fashion technology and clothing storage innovations.

"Home Cultures: The Journal of Architecture, Design, and Domestic Space": Explores domestic space and design, including discussions on wardrobes and clothing storage solutions.

3. Websites and Online Resources:

Dezeen: A design-oriented platform featuring articles and case studies on innovative wardrobe designs and clothing storage solutions.

Architectural Digest: Offers insights into interior design trends, including features on modern wardrobe designs and organization ideas.

Retail Design Blog: Provides information on retail space design, occasionally featuring articles on clothing store layouts and wardrobe innovations

4. Market Research and Industry Reports:

Euromonitor International or Statista: These platforms might offer market research reports on furniture design or home organization, including sections on modern wardrobes and clothing storage trends.