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A MULTIDIMENSIONAL ANALYSIS OF CUSTOMER SATISFACTION IN E-BANKING SERVICES

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Abstract
This theory presents a multi-layered investigation of consumer loyalty concerning e-banking administrations. In the quickly advancing computerized scene, understanding consumer loyalty is vital for e-banking suppliers. This study utilizes a complete methodology, using both quantitative and subjective strategies. Quantitative information is gathered through studies, zeroing in on elements, for example, site convenience, exchange speed, security, client care, and administration unwavering quality. Subjective information is assembled from top-to-bottom meetings, investigating clients' close-to-home reactions and discernments. Through factual examination and topical coding, the review recognizes key drivers and hindrances influencing consumer loyalty. Discoveries uncover nuanced bits of knowledge into the e-banking experience, revealing insight into regions for development. The complex structure gives a comprehensive view, empowering e-banking foundations to improve their administrations and designer contributions to more readily meet client assumptions. At last, this exploration adds to the streamlining of e-banking administrations and offers a significant asset for professionals and scientists in the field. This research is used secondary data to find the experience of the user and use this data to train the model. The accuracy of the model after training is found in this stage which improves the research and makes the research appropriate. The multidimensional analysis improves the accuracy of finding customer satisfaction. This project uses machine learning techniques to find the accuracy of the model and to solve the issue to improve customer satisfaction.

Keywords: multidimensional evaluation, Online Banking Services, reliability, efficacy, consumer happiness, innovative technical characteristics.

1. Introduction

1.1 Introduction

A careful examination of the client experience within this framework has been prompted by the revolutionary shift into digital platforms that has occurred in the modern environment of the banking sector. This research attempts to give a thorough analysis of the variables impacting client fulfillment by using an integrated strategy that takes into account elements like convenience, safety, connectivity, and communication. These results not only add to our knowledge about the changing nature of online banking but also provide banks with helpful information on how to improve their digital service offerings and personalize them to satisfy various client tastes and expectations.

1.2 Background

The background research for a multidimensional evaluation of client contentment in Online Banking Services" focuses on identifying the many factors that affect customer happiness in the context of Internet banking. This study aims to understand the complex interactions between technology, the level of service, accessibility, safety, and customer support elements and how they collectively affect consumers' overall happiness with online banking offerings [1]. The study aims to offer useful insights into boosting the reliability and efficacy of online banking platforms, eventually resulting in an improved and gratifying electronic banking interaction for clients by thoroughly studying these factors.

1.3 Problem statement

- It might be challenging to pinpoint the important dimensions as well as subdimensions that influence overall pleasure.
- It might be difficult to determine the proper weights for all dimensions or sub-dimension [2].
- It might be challenging to combine data from many sources and types, such as research, peer reviews, and logs of transactions.

1.4 Aim and Objectives

Aim

This project aims to examine several aspects of the e-banking experience while using multidimensional analysis to provide a thorough understanding of customer happiness and service improvement.

Objectives

- To investigate to see how users feel about the electronic banking services' level of reliability
- To determine the critical elements that have a major influence on Internet banking customer experience
- To analyze client categories according to their tastes and kinds of satisfaction

1.5 Research question

1. How do clients feel that online banking services are generally of high quality?
2. What were the main e-banking-related variables affecting client satisfaction?
3. How does client happiness relate to the accessibility of digital banking platforms?
4. How much do security and confidentiality concerns impact how satisfied customers are with online banking products or services?

1.6 Rationale

An extensive evaluation of the different elements affecting consumer happiness with e-banking services, including accessibility, safety, adaptability, and simplicity, is the goal of a multidimensional study of client happiness. This method offers a comprehensive insight into client preferences, assisting banks in improving their digital offerings to successfully address a variety of customer demands [3].

2. Literature Review

2.1 Introduction

This study dives into a complete investigation of consumer loyalty inside the domain of E-banking administrations, utilizing a multi-faceted methodology. Examining different sorts of aspects that influence client happiness, including ease of use, security, comfort, and responsiveness, this examination plans to give a nuanced comprehension of the variables driving or obstructing fulfillment. Through a fastidious investigation of these aspects, the review looks to uncover important bits of knowledge that can add to upgrading E-banking administrations and cultivating further developed client encounters, in this manner reinforcing the proficiency and viability of computerized financial stages.

2.2 Dimensions of E-Banking Services

In a multi-layered examination of consumer loyalty in e-banking administrations, a few key aspects assume a critical part in molding the general client experience. These aspects incorporate a scope of elements that add to consumer loyalty and commitment inside the domain of Internet banking.

Comfort and Openness: This aspect assesses how effectively clients can get to their records, perform exchanges, and get data through easy-to-understand connection points and every minute of everyday accessibility.

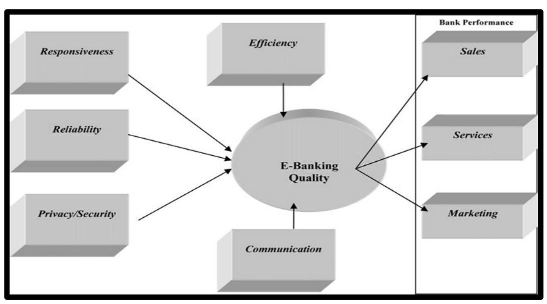

Figure 2.1: E-banking qualities

Administration Quality and Dependability: The effectiveness of exchange handling, exact execution of solicitations, and insignificant personal time add to the view of administration quality and unwavering quality [4].

Personalization and Customization: E-banking stages that proposition custom-made encounters in light of individual inclinations, needs, and monetary objectives upgrade consumer loyalty.

Correspondence and Backing: Successful correspondence channels, responsive client service, and convenient help add to settling issues expeditiously and fulfilling clients.

Development and Innovation: Standard updates, a mix of new highlights, and remaining at the bleeding edge of mechanical headways can upgrade fulfillment by giving advanced and developing help.

Data and Instruction: Accessibility of pertinent monetary data, instructional exercises, and assets assists clients with pursuing informed choices and feeling engaged.

Exchange Speed and Proficiency: Quick handling of exchanges and insignificant stand-by times add to a positive client experience [5].

Cost and Worth: Clear charge structures, cutthroat rates, and saw an incentive for cash are fundamental contemplations for consumer loyalty.

Cross-Channel Consistency: Giving a consistent encounter across different stages, for example, portable applications, sites, and ATMs, guarantees consistency and improves consumer loyalty.

2.3 Technology Acceptance and Adoption

The concentrate on "A Multi-faceted Examination of Consumer Loyalty in E-Banking Administrations" centers around the acknowledgment and reception of innovation in the domain of electronic banking. The exploration inspects the different components of consumer loyalty with e-banking administrations. It dives into the elements that impact clients' readiness to embrace and use these computerized financial stages. The concentration probably researches factors like usability, saw handiness, security, unwavering quality, and availability of e-banking administrations [6].

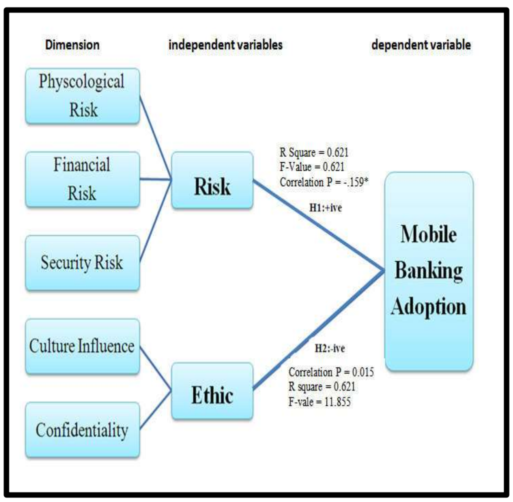

Figure 2.2: E banking adoption

Dissecting these aspects, scientists plan to uncover bits of knowledge into clients' perspectives and ways of behaving towards taking on e-banking innovation.

2.4 Service Quality and Customer Expectations

Through the context of Internet-based banking, the research study highlights the importance of service standards and consumer expectations. Investigators have been looking at the variables affecting consumer fulfillment as a result of the long-standing recognition by academics that the digital revolution of financial services has changed client experiences [7]. A key concept is service excellence, which measures how well e-banking services live up to or even exceed customers' expectations. Researchers have determined that aspects including reliability, reactivity, confidence, compassion, and tangibles are significant in determining how customers perceive the standard of service in online banking, depending on the framework known as **SERVQUAL**. The alignment of customer demands with service quality is essential. Due to the distinctive circumstances brought on by e-banking's electronic nature, customers now have higher expectations for smooth relationships, security of information, intuitive user interfaces, and assistance in real time. According to published research, the growing disconnect between client demands and the actual service quality might result in turnover and customer discontent.

2.5 Linkage to Aim

Examining previous research on consumer fulfillment in the framework of electronic banking, the available literature study creates a solid relationship to its aim. The investigation builds a foundation that shows the gaps and difficulties in comprehending client happiness through examining a variety of research relating to electronic banking, consumer behavior, along with service quality. The existing literature evaluation's strategic connection with the study's objectives serves to put the research, uncover pertinent customer satisfaction characteristics, and highlight the importance of the investigation in furthering the understanding of online banking services.

2.6 Literature gap

This literature has offered insightful information on several different facets of customer happiness and online banking facilities. The absence of a comprehensive study that analyzes client satisfaction inside the framework of online banking solutions from a multidimensional viewpoint, however, represents a noteworthy literature gap. Although earlier studies have looked into specific aspects such as service reliability, safety, usability, and simplicity, there is a lack of research that combines these aspects into a comprehensive framework. A complete grasp of how these factors interact to affect consumer satisfaction with online banking services is hindered by this knowledge gap [8]. Furthermore, the influence of new technologies like blockchain technology, chatbots, and neural networks on consumer happiness has received less consideration. Additionally, the vast majority of previous studies have concentrated on developed countries, ignoring the distinctive variations in satisfaction among consumers in emerging nations where technological progress and consumer preferences may vary greatly. Further research is required to determine how these context-specific cultural, economic, and legal aspects affect client fulfillment in electronic banking. Future studies could use an extensive and cohesive approach that takes into account several facets of customer delight in online banking solutions to fill this knowledge gap. This can entail taking into account the impact of both established service quality standards and innovative technical characteristics.

2.7 Summary

The investigation of the literature delves into the complex world of client fulfillment in the context of online banking services. The paper explores the multiple factors influencing customer satisfaction in the current online banking era, relying on a wide range of academic sources. It looks at the interactions between several elements, including service quality, technical user interface protection, convenience, and methods of communication, to affect how customers perceive businesses and their level of satisfaction. Previous investigations have shown how important personal interactions, frictionless transactions, and quick problem-solving are in creating a positive connection between clients and e-banking services. The analysis also highlights the crucial necessity for institutions to adjust to shifting client demands and the shifting significance of trust. The study establishes the framework for understanding the intricate nature of consumer happiness in e-banking by combining current knowledge, therefore indicating areas for further investigation and the tactical improvement of the services provided by e-banking.

3. Methodology

3.1 Appropriate Methods

The "**Search engine marketing analysis**" is done in this project for this task "**Deductive research approach**" is followed.

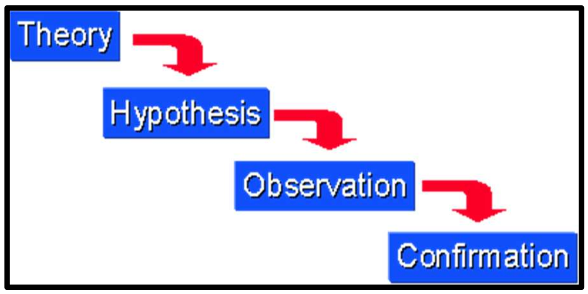

Figure 3.1: Deductive research

The "**deductive research approach**" creates a new hypothesis that is generated using the past theory. This research approach uses the past proven theory in the project to prove a hypothesis made in the research. The "**experimental research design**" is used in this project to gain the result of the research. This method gives full control to the researcher over the experiment [11]. This "**experimental research design**" shows the cause and effect of the project as per the research hypothesis.

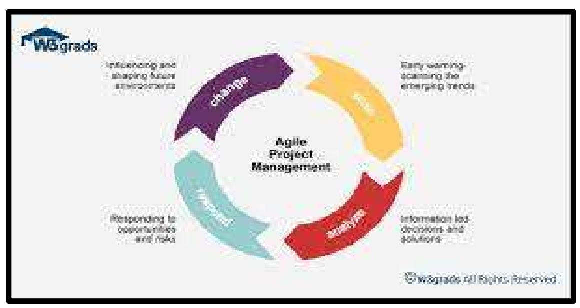

Figure 3.2: Agile project management

"**Agile project management approach**" is followed in this project. This is an iterative approach to making continuous improvements in the research. This agile approach is divided into two categories such as "**scrum" and "Kanban**". The scrum is used for the project with a fixed length, and the kanban is based on continuous improvement [12].

3.2 Justification of Chosen Methods

The "**Deductive research approach**" is appropriate in this project as this first generates a hypothesis and then uses the present theory to prove that hypothesis. The accuracy of the research approach is high as this uses the past proven theory to test the current hypothesis made in this project. The acceptance and the rejection of a theory are done as per the test or observation results.

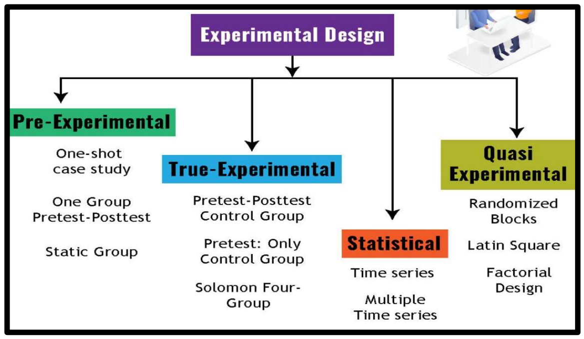

Figure 3.3: Research design

The "**experimental research design**" provides full control of the project to the research which makes this a good choice to obtain the result of the research. Various observations are done in this project which includes all present variables and improves the accuracy of the project. The multiple sub-domains of this research design allow the researcher to choose the appropriate process for obtaining the accurate result for the research [13]. The agile approach is followed in this project. This agile approach follows the requirements of the project, then develops the theory, and tests the theory, which makes this appropriate and effective for this project. These methods are appropriate for this project to find the customer experience and the proper deployment of these methods helps to find this accurately. This method of research improves accuracy and helps to remove the personal opinion of the researcher from the research.

3.3 Data Collection

Secondary data is used in this project. This secondary data of this project makes this project more effective. The data is tested and verified previously, improving the accuracy of finding customer satisfaction in E-banking services. Customer satisfaction depends on the quality of service provided to the customer and any issue in the service quality affects the customer experience. Secondary data is used for this project that includes all factors related to customer satisfaction and shows properly how this factor affects the experience of a user [14]. The project is completed using a Jupyter **Notebook. This** helps in this project to find the important factors of the data that affect the experience of a user. Various machine learning algorithms are used in this project for the multidimensional analysis of customer experience.

3.4 Ethical Consideration

The project is completed while considering all ethics that make this project acceptable. The data is the main component of this research to find the experience of a user. Unethical use of the data can create big issues, this is important to maintain data security in the project. Following ethics in the research makes the research acceptable and reduces issues like data leakage [15]. Customer financial data is confidential and the data security is maintained in this project which makes this project ethical.

3.5 Summary

The customer satisfaction analysis process is done in the following process. Data security is maintained in this project which makes this project ethical. Secondary data of customers related to E-banking is taken and stored privately. The analysis is performed in "Jupyter Notebook using

Python programming language". Various Machine learning algorithms are used in this project to find the customer experience in E-banking. This also helps to find the problem in E-banking and allows us to solve the issue. The research is completed by using the above-mentioned methods, ethics are also maintained in this project which makes this appropriate for this project.

4. Result and Discussion

4.1 Result

```
In [54]: # Importing Libraries of python
         import pandas as pd
         import numpy as np
         import seaborn as sns
         import matplotlib.pyplot as plt
```

Figure 4.1: Importing libraries

Important libraries of this project are imported in this stage, these libraries help in this multidimensional analysis.

```
In [55]: # Importing dataset
         df = pd.read_csv("E-Banking.csv")
         df.head()
Out[55]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

Figure 4.2: Importing libraries

The data set is imported in this stage; this data set is further used in this multidimensional analysis. Important details about the dataset are shown in the image such as the main columns of the dataset and the associated value to that column.

```
In [56]: df.tail()
Out[56]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSa
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	0	9627
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	10169
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	4208
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	9288
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	3819

Figure 4.3: Last five rows of the dataset

The last five rows of the data set are presented in this stage. This data set has 9999 columns.

```
In [57]: df.describe()
Out[57]:
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000

Figure 4.4: Dataset description

The description of the dataset is shown in this stage, numerical data is present in the data frame the description of the dataset shows this for each column.

```
In [58]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

Figure 4.5: Dataset information

The above image shows the information of the dataset such as the name of the columns present in the data set, non-null value count, datatype, and so on.

```
In [59]: df.isna().sum().sum()

Out[59]: 0

In [60]: df.duplicated('CustomerId').sum()

Out[60]: 0
```

Figure 4.6: Removing null value

The null value in the dataset creates problems in the analysis, this is necessary to remove all null values present in the dataset at the early stage to solve any error in the analysis. The above technique is used in this project to remove all null values from the dataset.

```
In [65]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 15634602 to 15628319
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   Surname          10000 non-null  object
 2   CreditScore      10000 non-null  int64
 3   Geography        10000 non-null  object
 4   Gender           10000 non-null  object
 5   Age              10000 non-null  int64
 6   Tenure           10000 non-null  int64
 7   Balance          10000 non-null  float64
 8   NumOfProducts    10000 non-null  int64
 9   HasCrCard        10000 non-null  int64
 10  IsActiveMember   10000 non-null  int64
 11  EstimatedSalary  10000 non-null  float64
 12  Exited           10000 non-null  int64
dtypes: float64(2), int64(8), object(3)
memory usage: 1.1+ MB
```

Figure 4.7: Dataset information after removing null values

The information of the dataset after removing the null value from the data set is shown in the above image. This data is further used in this project for multidimensional analysis of customer satisfaction in E-banking.

```
df['Geography'].value_counts()

France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64

values = {'Spain' : 0, 'France' : 1, 'Germany' : 2}
df.replace(values, inplace = True)
```

Figure 4.8: Value count per geographic location

The above image shows the data per geographic location, it is found that this data has three countries such as France, Germany, and Spain. In the next stage of this project, these values are converted from float to integer.

```
df['Gender'].value_counts()

Male      5457
Female    4543
Name: Gender, dtype: int64

values = {'Female' : 0, 'Male': 1}
df['Gender'].replace(values, inplace = True)
```

Figure 4.9: Male and female count

The number of males and females present in this project is shown in the above image, then these values are replaced by 0 and 1 to use that value further in this project.

```
df
```

	CustomerId	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	15634602	619	1	0	42	2	0.00	1	1	1	101348.88	1
1	15647311	608	0	0	41	1	83807.86	1	0	1	112542.58	0
2	15619304	502	1	0	42	8	159660.80	3	1	0	113931.57	1
3	15701354	699	1	0	39	1	0.00	2	0	0	93826.63	0
4	15737888	850	0	0	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...	...
9995	15606229	771	1	1	39	5	0.00	2	1	0	96270.64	0
9996	15569892	516	1	1	35	10	57369.61	1	1	1	101699.77	0
9997	15584532	709	1	0	36	7	0.00	1	0	1	42085.58	1
9998	15682355	772	2	1	42	3	75075.31	2	1	0	92888.52	1
9999	15628319	792	1	0	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 12 columns

Figure 4.10: Showing the dataset

The final data after replacing the geographic location with an integer value and the gender in the integer value is shown in this stage. This is done in this project to solve the error due to object data type this numeric data helps in this project for multidimensional analysis.

```
# correlation
corr = df.corr()
corr['Exited']

CustomerId        -0.006248
CreditScore       -0.027094
Geography          0.138714
Gender            -0.106512
Age                0.285323
Tenure            -0.014001
Balance            0.118533
NumOfProducts     -0.047820
HasCrCard         -0.007138
IsActiveMember    -0.156128
EstimatedSalary    0.012097
Exited             1.000000
Name: Exited, dtype: float64
```

Figure 4.11: Correlation

The correlation is found in this stage, this correlation of the data helps to know how each element is connected.

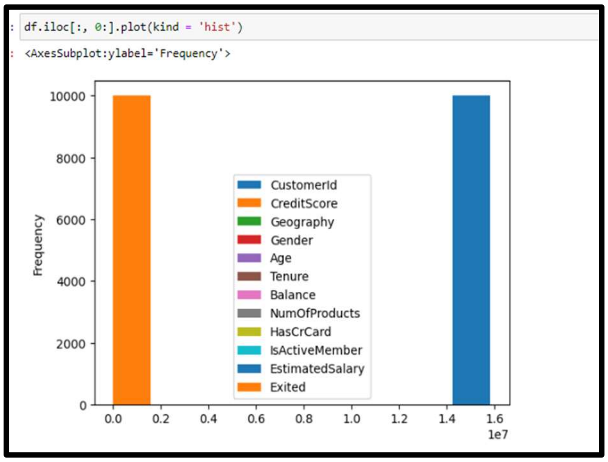

Figure 4.12: Histogram

The histogram is generated in this stage, this shows the multiple variables of the data in the "X-axis", and frequency in the "Y-axis".

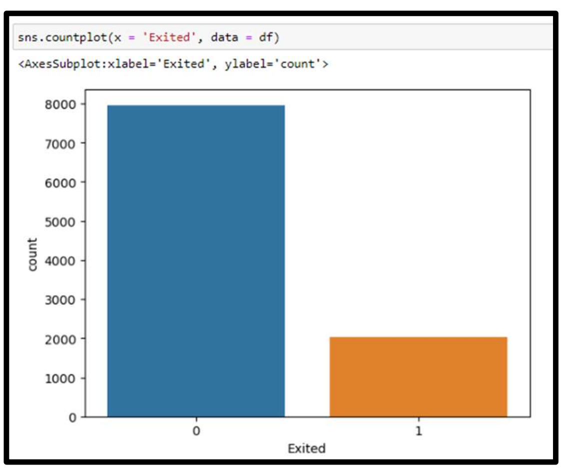

Figure 4.13: Bar plot

The bar plot generated and the “x-axis” of the plot show the column “Exited”, and the “Y-axis” represent the count.

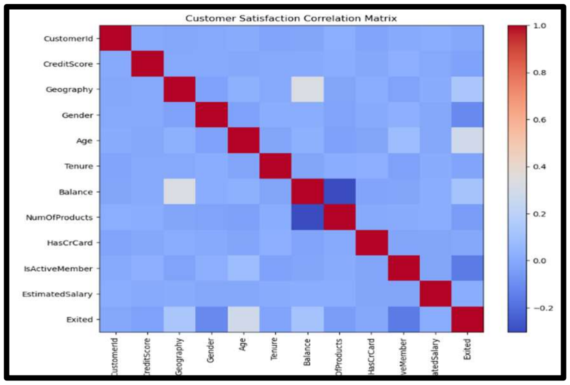

Figure 4.14: Correlation matrix

The correlation matrix is shown in this stage. This image shows the relationship of the different columns to each other.

```
# Definig Target Varibes
df.columns

Index(['CustomerId', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure',
       'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember',
       'EstimatedSalary', 'Exited'],
      dtype='object')
```

Figure 4.15: Showing columns of the dataset

The columns of the dataset are shown in this stage; the important columns are chosen for the analysis.

```
# Random Under Sampling
from imblearn.under_sampling import RandomUnderSampler

randon_under_sampling = RandomUnderSampler()

X_randon_under_sampling, y_randon_under_sampling = randon_under_sampling.fit_resample(x, y)
X_randon_under_sampling.shape, y_randon_under_sampling.shape

((4074, 11), (4074,))
```

Figure 4.16: Random under-sampling

Random resampling is the technique of transforming the dataset randomly. This is divided into two categories such as “**random under-sampling, and random over-sampling**”. The random under-sampling approach is shown in this stage that deletes examples in the “majority class”.

```
# Random OverSampling
from imblearn.over_sampling import RandomOverSampler
random_over_sampling = RandomOverSampler()

X_random_over_sampling, y_random_over_sampling = random_over_sampling.fit_resample(x, y)
X_random_over_sampling.shape, y_random_over_sampling.shape

((15926, 11), (15926,))
```

Figure 4.17: Random over-sampling

The "random oversampling" technique is shown in this stage that is used to replicate the examples to the "minority class".

```
# Primary data
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state= 1, test_size = 0.10)

# Under_sample_data
x_train_rus, x_test_rus, y_train_rus, y_test_rus = train_test_split(X_rus, y_rus, random_state= 1, test_size = 0.10)

# Over_sample_data
x_train_ros, x_test_ros, y_train_ros, y_test_ros = train_test_split(X_ros, y_ros, random_state= 1, test_size = 0.10)
```

Figure 4.18: Training data

The data is trained in this stage, and the training of primary data, undersample data, and over-sample data is done in this stage.

```
# Model Support vector classifier
from sklearn.svm import SVC
model = SVC()

x_train[['EstimatedSalary', 'Balance', 'Tenure', 'Age', 'CreditScore']] = scale.fit_transform(x_train[['EstimatedSalary', 'Balanc
model.fit(x_train, y_train)

SVC()

x_test[['Balance', 'EstimatedSalary', 'Age', 'Tenure', 'CreditScore']] = scale.fit_transform(x_test[['Age', 'Tenure', 'Estimated

y_pred = model.predict(x_test)
```

Figure 4.19: SVC

The SVC is the "supervised machine learning algorithm" used in this project for the classification task. This SVC maps the data point in the "high dimensional space" and then divides that data into different classes.

```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

confusion_matrix(y_test, y_pred)

array([[789,   0],
       [211,   0]], dtype=int64)
```

Figure 4.20: Confusion matrix

The confusion matrix generated in this stage is used to measure the performance of machine learning algorithms.

```
print(classification_report(y_test, y_pred))

              precision    recall  f1-score   support

           0       0.79      1.00      0.88       789
           1       0.00      0.00      0.00       211

    accuracy                           0.79      1000
   macro avg       0.39      0.50      0.44      1000
weighted avg       0.62      0.79      0.70      1000
```

Figure 4.21: Performance measurement

The performance of the SVC model is shown in this stage, the accuracy of the model is 0.79.

```
# Under sampling
from sklearn.svm import SVC
model = SVC()

x_train_rus[['Balance', 'EstimatedSalary', 'Age', 'CreditScore', 'Tenure']] = scale.fit_transform(x_train_rus[['Balance', 'Estima
model.fit(x_train_rus, y_train_rus)

SVC()
```

Figure 4.22: Fitting under-sampling data into the SVC model

The under-sampling data is fit into the “support vector classifier model” that uses this data and trains the model.

```
print(classification_report(y_test_rus, y_pred_rus))

              precision    recall  f1-score   support

           0       0.47      1.00      0.64       192
           1       0.00      0.00      0.00       216

    accuracy                           0.47       408
   macro avg       0.24      0.50      0.32       408
weighted avg       0.22      0.47      0.30       408
```

Figure 4.23: Accuracy

The accuracy of the SVC model using the under-sampling data is shown in this stage the accuracy is 0.47.

```
# over sample
from sklearn.svm import SVC
model = SVC()

x_train_ros[['Balance', 'EstimatedSalary', 'Age', 'CreditScore', 'Tenure']] = scale.fit_transform(x_train_ros[['Balance', 'Estima
model.fit(x_train_ros, y_train_ros)

SVC()
```

Figure 4.24: Fitting over-sampling data into the SVC model

The over-sampling data is fitted into the model then the accuracy of the model is calculated.

```
print(classification_report(y_test_ros, y_pred_ros))

              precision    recall  f1-score   support

           0       0.49      1.00      0.66       778
           1       0.00      0.00      0.00       815

    accuracy                           0.49      1593
   macro avg       0.24      0.50      0.33      1593
weighted avg       0.24      0.49      0.32      1593
```

Figure 4.25: Accuracy

The accuracy of the model after training the model using the over-sampling data is 0.49. This accuracy shows how accurately the model can predict the value, this value of accuracy shows the model's efficiency to find customer satisfaction.

4.2 Discussion

"**Multi-dimensional analysis**" is used to order data in the database; this is done by making a proper arrangement of the main contents of the data. This arrangement is done and shown in this project after the proper arrangement this data can show all important factors of the data properly. The analytical question related to the data can be solved by using this method. The answer about the experience of a user in E-banking can be obtained rapidly using this method. The multidimensional analysis first assembles the data, then groups that data into different segments, after that the data is proportioned into different noticing, the actuarial time factor is prepared, factor quality is measured, and last a schema is built to place that data [16]. This project includes different factors such as the age of a customer, monthly salary, geographic location, credit amount, gender, tenure, balance, and so on. All of these factors are considered for this multidimensional analysis to analyze the experience of a user in E-banking services. Each factor has an impact on the experience of a customer. This multidimensional analysis considers all of these factors that improve the accuracy of the model to predict customer satisfaction.

Customer satisfaction depends on various factors and this is different for customers living in different locations. The expectation of a user varies from place to place, proper analysis of the market helps to know all these factors and to know the effect of that on the customer experience. Maintaining all the factors is necessary to improve the experience of a user [17]. This research includes all factors that can affect the user experience and show the area of improvement to improve customer satisfaction. Various machine learning algorithms such as random oversampling, random undersampling, and SVC are used to properly train and to find the accuracy of the model. Random undersampling and random sampling is the technique of choosing samples randomly for the transformed dataset.

The random under-sampling removes some examples in the majority class, and the random over-sample duplicates some examples in the minority class. This technique is used for the generation of transformed data sets which are fitted in the machine learning model SVC to find the accuracy of prediction. The prediction shows how effectively the model can measure the experience of the user and the factor affecting the experience using this model. The user experience can be improved by using this method for identifying the lacking area in the research. The user experience is measured using these techniques [18]. The model has good accuracy to predict the user experience while considering all important factors that affect the user experience of a customer.

5. Conclusion

5.1 Critical Evaluation

The review's multi-layered investigation of consumer loyalty in e-banking administrations offers a complete view. It adroitly investigates different aspects affecting consumer loyalty, upgrading understanding. The strategic methodology's complexities and impediments warrant examination [9]. Furthermore, a greater example size could support the review's power. Despite these places, the examination contributes significant bits of knowledge to the e-banking area's client-driven techniques, propelling our cognizance of this developing scene.

5.2 Summary of the Achievements

The discoveries of this study could have suggestions for monetary organizations looking to upgrade their e-banking contributions and increment consumer loyalty. With the technique of understanding the variables driving innovation acknowledgment and reception, banks can fit their administrations to be more likely to address client issues and inclinations. In outline, this exploration gives a complete investigation of consumer loyalty in e-banking administrations, investigating the diverse perspectives that impact innovation acknowledgment and reception concerning computerized banking.

5.3 Research recommendations

It advises future study that uses a larger sample size to examine how demographic variables affect consumer satisfaction with e-banking [10]. Examine the relationship between service quality parameters and overall satisfaction, as well as the way technological proficiency affects satisfaction. Also, evaluate the extent to which customizable interfaces improve the electronic banking experience.

5.4 Future work

Future studies on the multidimensional evaluation of customer feedback in electronic banking Solutions may examine the changing environment of digital banking with an emphasis on cutting-edge innovations like chatbots powered by artificial intelligence, blockchain technology security, and tailored financial advice. Further research through the way cultural along with demographic factors affects consumer satisfaction with e-banking. It also includes the incorporation of immersive or augmented reality functions into electronic banking platforms, which could be very helpful in determining how to raise client fulfillment in the internet-based banking industry.

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