**Capstone Project:**

**Understanding Cyber Security and Safety Perceptions**

**for**

**Digital Payments and E-Services**



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# Executive Summary

The Capstone Project for EPABA Batch 05 focuses on investigating the factors that impact cybersecurity in online transactions, particularly in the context of digital payments and e-Services. The study aims to understand consumer perceptions of safety in these transactions and analyse how various factors influence the adoption of digital payments and e-Services. Additionally, the project aims to identify associations with demographic variables and address the challenges hindering the widespread adoption of digital payments and related e-Services. The insights gained from this analysis will contribute valuable information to enhance cybersecurity measures and facilitate a smoother transition to digital payment methods and e-Services.

# Introduction

In today's digital world, using things like online payments and services on the internet has become really common. But, as we do more things online, like paying for stuff, there's a worry about how safe it is. This project, part of EPABA Batch 05, is all about figuring out what makes online transactions safe or risky, especially when it comes to digital payments.

A lot of people are concerned about using digital payments. Some don't know much about the risks of cyber fraud, and others worry they might lose money when they pay for things online. We want to understand how different groups of people, like those of different ages, incomes, and jobs, feel about using digital payments. This way, we can come up with good ideas to encourage more people to use digital payments and make sure it's safe.

To get all this info, we're talking to people and asking them questions through surveys. We want to know what they think about digital payments, if they know about cyber fraud, and if their age, income, or job influences how they use these services. After collecting all this info, we'll study it closely to find out what patterns we can see and come up with practical suggestions. Our goal is to make digital payments widely accepted and safe for everyone. The process involves talking to different people and using surveys to get a complete picture, and then carefully studying the data to find useful insights.

# Objective

The objective of this project is to investigate and understand the factors influencing cybersecurity in online transactions, with a specific focus on digital payments and e-Services. Leveraging the analytical tools and methods acquired during the EPABA program, our study aims to answer key questions through exploratory analysis, shedding light on various dimensions of consumer behavior and perceptions.

Key Questions to be Addressed

## Exploratory Analysis

* How do individuals of different age groups, income levels, and occupations engage with digital payments and e-Services?
* What patterns emerge when we explore the data based on demographic factors such as age, income, and occupation?

## Cybersecurity Concerns

* To what extent are people concerned about the cybersecurity of online transactions, particularly in the context of digital payments?
* How do these concerns vary across different demographic segments?

## Awareness of Fraud Possibilities

* How aware are individuals of the possibilities of cyber fraud in the realm of digital payments and e-Services?
* Are there demographic factors that influence awareness levels?

## Likelihood of Financial Loss in Fraud

* Who is more likely to experience financial losses in cases of cyber fraud during online transactions?
* Are there identifiable patterns related to age, income, or occupation that correlate with a higher likelihood of losing money?

## Usage of Online Learning Platforms

* How are people utilizing online learning platforms, and is there a correlation between their engagement with digital payments and participation in online learning?
* Can demographic factors provide insights into the adoption and usage patterns of online learning platforms in conjunction with digital transactions?

By addressing these questions through a comprehensive analysis of the gathered data, we aim to contribute valuable insights that can inform strategies to promote the safe adoption of digital payments, mitigate cybersecurity risks, and understand the intersection between digital transactions and online learning behaviours.

# Methodology

Figure 1 Project Methodology

# Data Collection

## Target Population

To capture user perception over wide age group, income group and service group, we targeted population which can cover college students, professionals, home maker as well as those who are in their matured stage of service.

College going students provide unique insights on their comfort and concern over usage of various online platforms for payment, purchase and learning. Home maker provides very distinct view being different challenges faced by them which may include type of joint or nuclear family. Professionals from various fields bring different perspectives for their experience and challenges faced by them. Businessman by economic trends market dynamics may give different insight of online platform usage which may have different perceptive after covid19 and their comfort of online transaction over cash transactions.

To ensure respondents comfort for answering relevant questions we limited questions which are not specific any individual for example income data, business data, family type, etc. This will ensure data privacy as well.

A group of text boxes

Description automatically generated with medium confidenceGeography for the sample is planned in Ahmedabad and Target sample size was at least 100+

## Survey Type

Our intention was to have primary data for our project hence out of various options of face to face interview, paper survey questionnaire, we decided to go for google survey and defined our actions accordingly.

## Survey Questionnaire Design

While designing questions we have targeted following information and accordingly divided various sections in google form.

Figure 2 survey questionnaire sections

1. Reponses by various factors : Age, Income, Occupation
2. How people are concerned about Cyber Security
3. How much people are aware about possibilities of fraud
4. Who are likely to lose the money in fraud

Questionnaire has major eight sections. Where in we tried to collect information regarding respondents view related to Online transactions and if they do so we asked other questions.

If respondents is not doing online transactions then we did not asked any other questions other than understanding demography. We also created sections for various online usage which includes Online Payment, Online Services, Online Learning. For every section we asked respondents if they are using particular online platforms and if the answer is no then we route questions to next section. The questionnaire covers 54 questions combining all sections.

A screenshot of a computer

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Figure 3 Google survey form sample page

## Survey Method

Due to time constraints, we decided to go for online survey instead of personal survey to various area. We agreed that google survey form sharing via email, WhatsApp or other social media can have wider reach and data can be collected in shorter duration. So we emailed our google survey form survey as well as share link on whatsapp.

Prior to sharing google survey we have taken dummy trials on how user feels and how much time user need to spend on filling survey.

Few close respondents were interviewed as for first pilot run of survey form and noted their suggestion to make it more convenient for respondents to answer questions.

Data Collection period was planned for maximum two weeks, however we could collect most of the data in one week of time.

## Data Collection, Cleaning and Validation

Google form (Joshi, 2023) data have been collected in Excel file which have been further reviewed for cleanliness, some of responses which were descriptive were segregated and added extra columns for categorising them.

As our data collection was categorical most of answers we got were “Yes” or “ No” and in some questions we also tried to measure depth of particular variable hence options were mentioned which were ordinal in nature. We kept it ordinal with an intention to find out users strong associations for particular variable, however in our analysis we did not focused much on same and converted original data to “ Yes” and “ No” only. For example for a question’s response we asked about frequency of usage in which respondents were having options to answer either “ Regularly “ , “ Occasionally” , “Rarely” , “Never” so for the said question and its importance as critical variable we only considered value as “Yes” for responses “ Regularly” and for reaming responses like “ Occasionally” “Rarely” “Never” we gave value “No”.

For deriving Exploratory Analysis we need to clean data further, however for Predictive Analysis we converted data to Binary. So “Yes” responses have been given value as “ 1” and “ No” responses have been given value as “0”.

We have used clean data to run in “ R Program” to validate if this is working fine, for which our results were good, however we could noticed that as data variables are too large it might be good break data in certain sections for in depth analysis.

## Data Primary Analysis and Improvements

On duly validation of data various predictive models run which were working fine in terms of results however while inferring these variables we have noted it does not give us true meaning of our objectives which we were looking, at this joint we took help of mentor and noted that as data is skewed towards more “ Yes” and little information about “ No” all results are also skewed towards “ Yes” hence its not giving true inferences. In other words our data was unbalanced and need to be balanced. So we use SMOTE function and balanced data for further analysis.

### SMOTE

**Synthetic Minority Oversampling Technique** is called as **SMOTE** in short form. SMOTE uses nearest neighbouring approach to generate minority class samples. There are two methods to use SMOTE , Under sampling and Over Sampling, when we have large data set for example 1000 responses in which data is skewed towards one specific response for example 800 responses are “Yes” and 200 responses are “No” then we go for under sampling method in which majority class data is reduced to lower size for example 800 becomes 400 and so we avoid any further skewness of data. We may have to go for few trials before we reach to particular number of data set, which is usually done on test data.

Other method is Oversampling method in which we increase minority class data by synthetically duplicating responses. Method is used is of k-nearest neighbours. Algorithm identifies feature vector and its nearest neighbour the difference between two is calculated and multiplied with random number 0 and 1 and new data point is created , this process is repeated until desired balance is achieved. There are some limitations also of SMOTE which need to be noted while using this tool. The limitations is due to data which is not new but from the sample data so it does not provide any new information, some times it can overfit also . If data has issue on separation of various category then this may not beneficial , this can also lead to different inferences when data is too small or too large.

Considering all above points we have validated our model results from SMOTE Test data and noted that it provides us logical and practical inferences of our study hence we accepted SMOTE data for further analysis. We have referred books/materials from library (IIM Library, 2023)

A diagram of a pie chart

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Figure 4 SMOTE data method

(Kegelmeyer, 2002)

(Managing imbalance Data Set with SMOTE in Pythone, 2020)A graph of a bar and a bar of glass

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Figure 5 SMOTE data types

# Data Analysis

## Exploratory Data Analysis:

For the Exploratory Data analysis we used Tableau software, where in main validated file has been uploaded without conversion to binary. Various worksheets created for all the target variables. Used Tableau inbuilt features of calculating % of specific variable out of total variable. Some data where having multiple responses (Ordinal Type or Different Category Type), Tableau inbuilt feature of splitting of data and pivot table helped for understanding each variable separately. All respective worksheets have been combined in Dashboard for overall inference about specific variables and related responses.

## Online Application Users



Figure 6 Digital Platforms

We studied how many users are using online platform for various applications like payment, purchase, or learning. Figure 7 illustrates about

Online Users for Payment Applications is 96%

Online Users for Purchase Applications is 93%

Online Users for Learning Applications is 74%

So from Figure we can infer that Online payment applications is most significant among other applications.

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Figure 7 Online Application Users

## Reasons for not using Online Applications

## Non-users of Online Payment Applications

From Figure 8 we can infer that those who are not using Online Payment is because they feels risk of Fraud during transactions and some of them don’t use because of transaction charges.

* Reasons for Not Using
  1. Risk of Fraud 82%
  2. Due to Transaction Charges 18%



Figure 8 Reasons for not using online payment.

## Non-users of Online Procurement Applications

From Figure 9 we can understand about reasons of respondents who are not using Online eServices i.e. online procurement and following are main reasons.

* Reasons for Not Using
  1. Privacy and Security Concern 63%
  2. Lack of In-Store Engagement 15%
  3. Vulnerabilities to Frad 11%
  4. Lack of Knowledge 7%
  5. Shipping Problems 4%

We can summarise that privacy and vulnerability are major factors of user not using Online Procurement platforms.

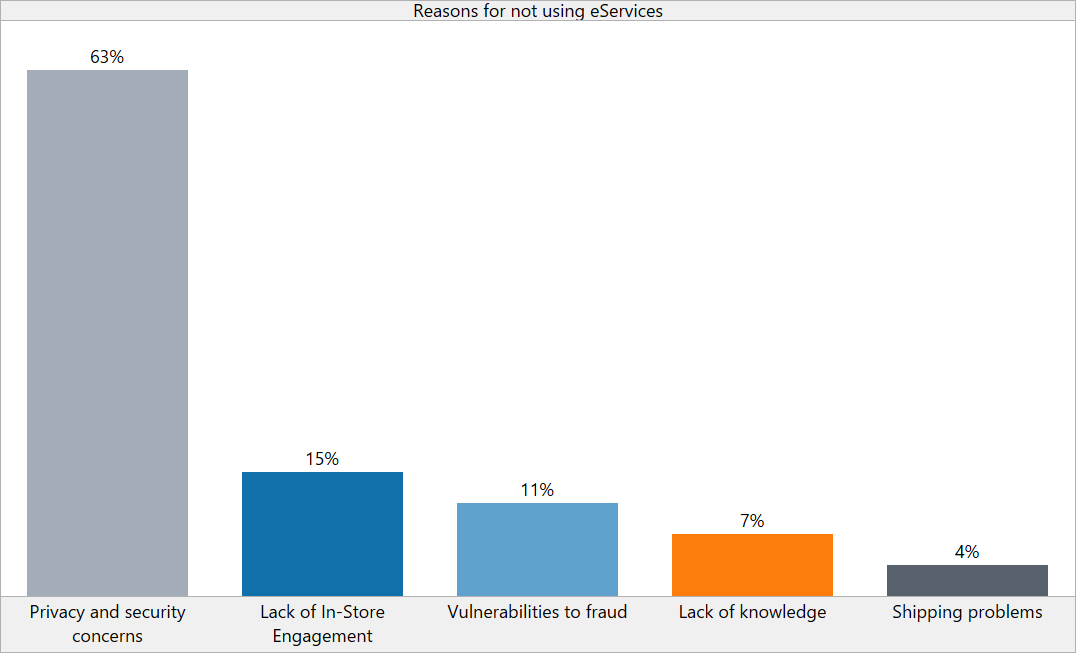


Figure 9 Reasons for not using eServices

## Non-users of Online Learning Applications

Figure 10 Illustrates about top two reasons for not using online learning applications. We can see that users does not feel risk of cyber fraud for the online learning, however they don’t use because of following two main reasons, we may infer that as learning applications use may not required commercial transactions as compulsory, user may not see risk of cyber fraud. Some of respondents have express about their fear of unknown, this bring interesting insights into understanding how Online learning applications can be made more popular to reduce fear, and that’s an opportunity for further research in this area, however as our objective is limited we consider this point for further research.

* Reasons for Not Using Learning Applications
  1. Lack of motivation 80%
  2. Fear of Unknown 20%

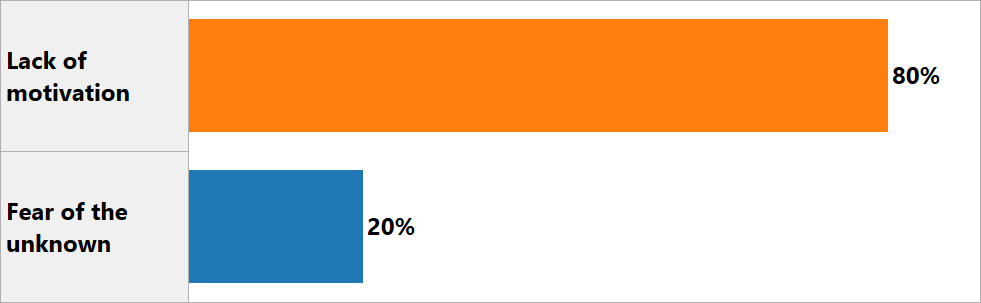


Figure 10 Reasons for not using Online Learning Applications

## Demography

Respondents Demographic profile is well illustrated in Figure 11 , this provides clear representation of diversity regarding gender, age, education, occupation and income. The Majority of respondents are male and representing 75% of total respondents. Among age category we can see that nearly half of total respondents are Young having age less than 25 years, followed by 26% between age of 25 to 40 and 26% between age of 40 to 61. This means our respondents covers well spread diversity among different age groups which will help us for understanding different perspectives of their experiences.

Similarly we can see that almost half of respondents are students and remaining most are working professionals with very little who are home maker. With this two distinctive class we will have interesting perspective of risk aversion capability between students and professionals as they will be at different stages of their experience.

We can also see that most respondents are well educated and 21% represents even higher education, this also brings good information about their awareness related to online applications as well as various tools for performing transactions and that may not limit their opportunities if they wish to use online services, this is very important factor for our study.

Income category analysis suggests that most respondents are of middle income categories, this can be interesting study during analysis about their online platform usage frequency, as it might be possible that higher income category respondents may like to use traditional way of transaction instead of online transaction due to high risk of cyber fraud at the same time lower income category respondents may concern more of loosing money in case of cyber fraud as their entire budget may jeopardize while evaluating risk vs benefit.

We will be having interesting insight of various demographic factors while we do statistical analysis with help of various predictive analysis tools.

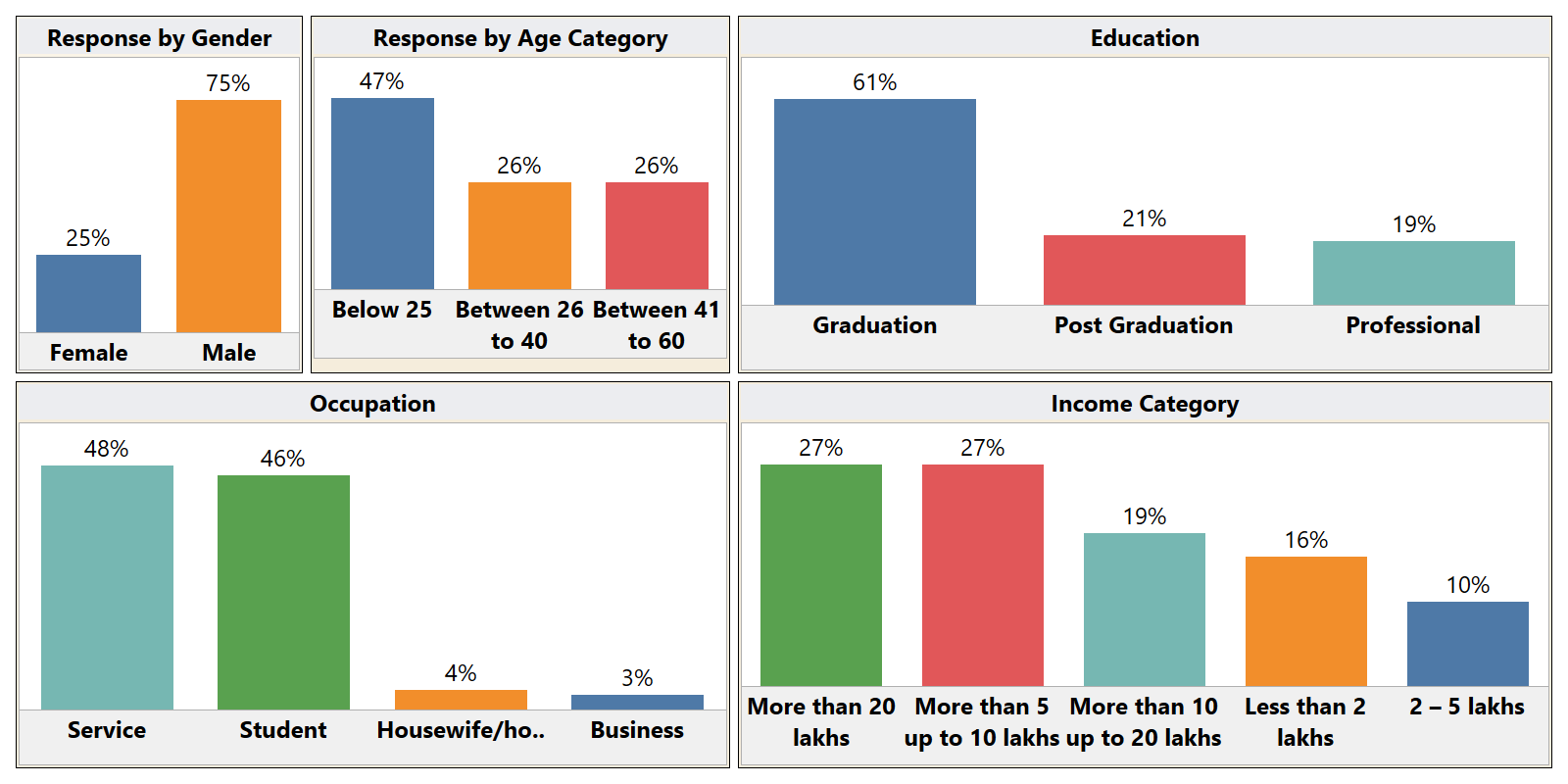


Figure 11 Demographic information of the data

## Transactions Methods Used for Online Payment

While analysing further about which online payment method is most popular among users, we found that UPI accounted for maximum % of user which is 63% among total respondents.

We studied what is current trend in India and following is insight from published economic survey 2023 in which UPI accounted for 52% of total digital transactions. Figure 12 illustrates about UPI payment growth year over year which is published by website “money control “ in their article “ Economic Survey 2023: UPI accounted for 52% of India's total digital transactions in FY22” where in data source is from “ National Payments Corporation of India (NPCI) ”

A graph with numbers and a line

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Figure 12 UPI Transactions in India

(Economic Survey 2023, 2023)

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Figure 13 online payment methods

Other popular payment methods are NEFT 24% followed by IMPS 9% and RTGS 4%, this says about convenience of UPI payment methods and credit goes to ease of doing online transactions which also becomes good opportunities for cyber fraud.

## User Experience about Cyber Fraud

From Figure 7 we have noted that 96% of respondents are using online payment platforms, so we also studied while doing so what is their experience in response to cyber fraud. Figure 14 illustrates that 13% of respondents have experienced cyber bullying while performing online payment transactions and 16% have lost money who has experienced cyber bullying. Overall percentage of respondents about cyber bullying concern is as high as 65% as they are very much concerned about cyber bullying. Around 24% of respondents has little concern about cyber bullying and 11% are risk takers as they know they should be concerned about cyber bullying but they are not concerned, primary reason for the could be because nearly 50% of respondents are young generation.

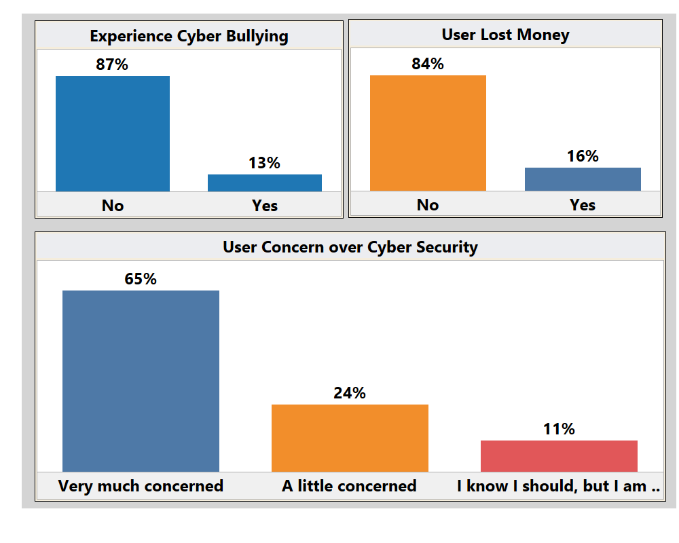


Figure 14 user experience and perception towards cyber fraud

## User Experience about Cyber Fraud

While performing Online Payment transactions, there are several incidents wherein users have queries for which they need help for the resolution, through questionnaire we tried to find out whether they are concerned about using Artificial Intelligence Tools like Chatbot ? as during interaction with Chatbot they might need to provide confidential information and if so how are they perceiving their risk about cyber fraud during same interaction.

From Figure 15 we can note that 26% respondents are frequently using chatbot as their tools for resolving queries. Around 35% of respondents uses chatbot sometimes and 39% of respondents never used chatbot. With this we can infer that chatbot is taking popularity as one important tool for resolving queries quickly. We can also infer from figure that 43% felt that its very useful tool for them and 41% believes that it may compromise their privacy while using such Artificial Intelligence tool, there are 32% of respondents says about their concern over privacy, however remaining respondents seems more comfortable, so we can infer that there is good opportunity for establishing more AI tools and more awareness among users for making it more effective. More research in this area will be very interesting and can bring different insights of digital payment and artificial intelligence collaboration.

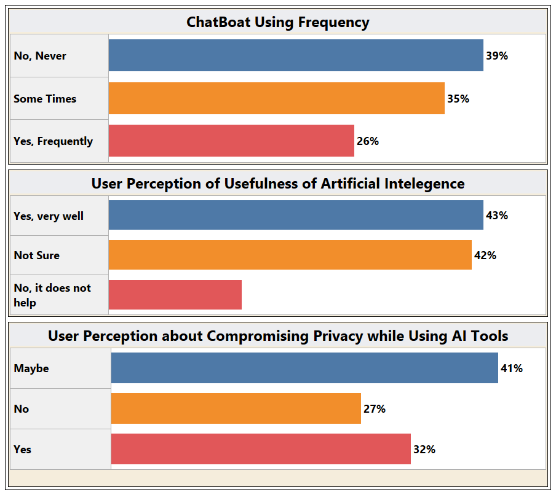


Figure 15 usage of chatbot (artificial intelligence tools)

## Authentication Methods Used

While performing online payment transactions we tried to find out how much user is aware about risk involved when using Public network or when they try to use Web address which are not secured i.e. https://

Figure 16 provides very important information about user’s risk exposure as 54% of respondents uses public network some times if we add 5% who uses regularly this total is almost 60% which shows very high exposure about Risk while using public network. Around 19% respondents do not ensure whether website is secured or not that further added their risk of cyber fraud. However we can note that 42% ensures that web address is secured while they perform online transactions, followed by 38% who uses secured web address some times, we can infer from this about well awareness among users for using secured web address while performing online transactions.

Finger print authentication is most popular authentication method which tells about most users using mobile as their instruments for online transactions, followed by security pin, password and faceid. A screenshot of a computer screen

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Figure 16 authentication method and secured webservice usage

## Online Buying

Online buying or ecommerce is referred as eServices for our project where in we focused on understanding users perspective towards cyber fraud related concern and if so what are the factors effecting it.

From Figure 17 we can understand that 92% online buyers are aware about cyber fraud as they believe cyber fraud can happen during performing online transactions as it correspondence to commercial transactions. When we tried to perceive which period has inspired them for going for online buying is period post 2015 and their preferred platform is Amazon as 93% respondents voted Amazon compared to other options. Their inclination towards online buying is primarily due to Lower prices, convenience and wide product availability. However though it looks on prima facie about time savings, but user has considered it as least factor as its felt by 7% as time is saved during performing online buying transactions.

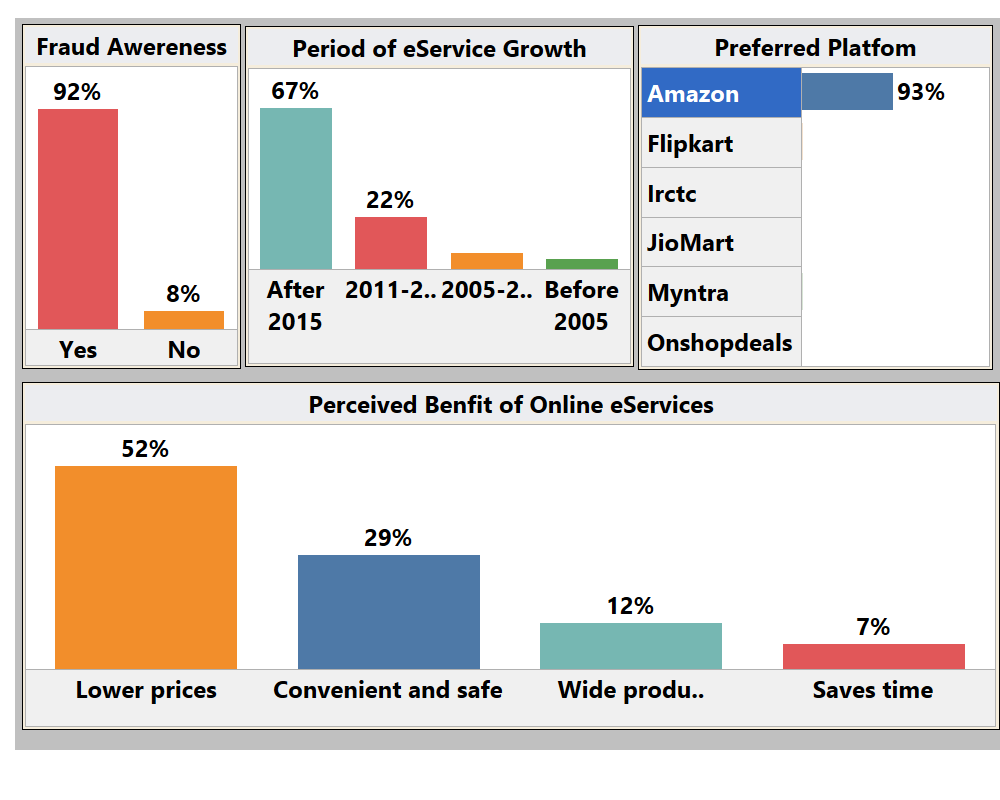


Figure 17 online buying (eservices) experience

## Online Learning

Along with user perception about cyber fraud in Online Learning, we also tried to find out which platform is most popular among user.

Figure 18 Illustrates that out of total respondents 74% of respondents are using online learning platforms and their preferred learning platforms are YouTube (46%) , Udemy (17%), Coursera(14%). Its interesting to know that approximately 1/3 of respondents were using online learning platforms even before Covid19 and approximately 2/3 of respondents started online learning post covid19. Users perception about fraud in On line learning is about 13% and most of them feels it has not much risk compared to Online payment and Online Buying.

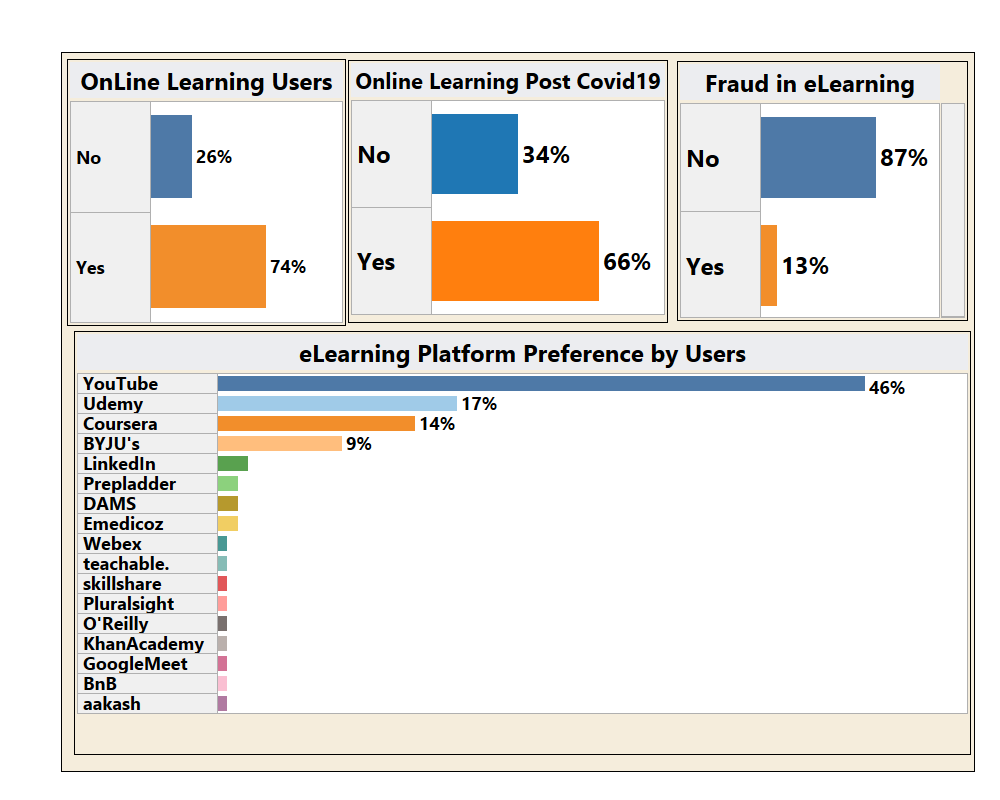


Figure 18 online learning platforms

## Predictive Analysis

## Logistic Regression Model to find how people are concerned.

## Selection of Response Variable

The selection of the response variable as a binary indicator of whether people are concerned or not is based on several considerations aligned with the goals of the analysis

* Clear Focus: A binary choice simplifies the analysis, making it clear whether individuals express concern about security on the internet.
* Alignment with Research Question: It directly relates to our research goal of understanding factors influencing people's concerns.
* Compatibility with Logistic Regression: Binary responses work well with logistic regression, a tool suited for predicting outcomes with two categories.
* Easy Interpretation: Coefficients in logistic regression directly link to the likelihood of expressing concern, making results easy to understand.
* Actionable Insights: The binary variable guides targeted strategies to address concerns and promote positive behaviors.
* Statistical Suitability: Binary outcomes simplify statistical analyses, facilitating model fit assessments and hypothesis testing.
* Practical Relevance: Decision-makers often seek insights on the prevalence of concerns, aligning with real-world needs.

## Explanatory Variable Selection:

Explanatory variables were selected to find pattern of how demographic information affects people’s concern about security on internet

|  |  |
| --- | --- |
| **Response Variable** | **Values** |
| Concern\_Binary | 1 for Concerned , 0 for less concerned |
| **Explanatory Variables** | **Values** |
| is\_male | 1 for male, 0 for not male |
| is\_female | 1 for female, 0 for not female |
| age\_group | 1 for below 25, 2 for 25-40,3 for above 40 |
| is\_graduate | 1 for graduate, 0 for not graduate |
| is\_postgraduate | 1 for postgraduate, 0 for not postgraduate |
| is\_schooling | 1 for schooling, 0 for not schooling |
| is\_other\_education | 1 for other education, 0 for not other education |
| is\_business | 1 for business, 0 for not business |
| is\_service | 1 for service, 0 for not service |
| is\_student | 1 for student, 0 for not student |
| is\_homemaker | 1 for homemaker, 0 for not homemaker |
| income\_group | 2 – 5 lakhs: 1, Less than 2 lakhs: 2, More than 10 up to 20 lakhs:3,More than 20 lakhs:4,More than 5 up to 10 lakhs:5 |

Table 1 Variable Selection for Logistic Regression Model to find how people are concerned.

## Data Preprocessing:

* Converted columns like age\_group and income group from text response like

|  |  |
| --- | --- |
| **Income Group** | **Variable** |
| 2 – 5 lakhs | 1 |
| Less than 2 lakhs | 2 |
| More than 10 up to 20 lakhs | 3 |
| More than 20 lakhs | 4 |
| More than 5 up to 10 lakhs | 5 |

Table 2 income group encoding in logistic model

|  |  |
| --- | --- |
| **Age Group** | **Variable** |
| Below 25 | 1 |
| Between 26 to 40 | 2 |
| Between 41 to 60 | 3 |

Table 3 age group encoding in logistic model

## Data Scaling:

Since the response variable concerned was more skewed toward more people concerned , we use upscaling techniques in the R code to upscale data using library caret

## One-Hot Encoding:

* Introduced dummy columns representing different categories to capture categorical information

e.g. is\_male, is\_female,is\_studen

## Collinearity Assessment

* Use Variance Inflation Factor (VIF) analysis to identify and address multicollinearity among explanatory variables.
* Removed variables with high VIF values to improve model stability and interpretability.

## Variable Selection

* Selected is\_student and age\_group as these were the statistical significant data with the sample data

## Model Building

Built logistic model using

|  |
| --- |
| summary(final\_model)  # Call:  # glm(formula = concern\_binary ~ age\_group + is\_student, family = binomial,  # data = data)  #  # Coefficients:  # Estimate Std. Error z value Pr(>|z|)  # (Intercept) 5.0151 1.6287 3.079 0.002076 \*\*  # age\_group -1.7268 0.6137 -2.814 0.004897 \*\*  # is\_student -3.5396 1.0728 -3.299 0.000969 \*\*\*  # ---  # Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1  #  # (Dispersion parameter for binomial family taken to be 1)  #  # Null deviance: 142.79 on 103 degrees of freedom  # Residual deviance: 128.11 on 101 degrees of freedom  # AIC: 134.11  #  # Number of Fisher Scoring iterations: 4  # Conclusion --------------------------------------------------------------  # Overall, this model suggests that both 'age\_group' and 'is\_student'  # are important predictors of the binary response variable 'concern\_binary',  # and the model provides a good fit to the data |

Code Snippet 1 Logistic model

## Model Evaluation

Model checked for accuracy by following metrices.

|  |  |  |
| --- | --- | --- |
| **Metric** | **Training Data** | **Validation Data** |
| TP | 25 | 37 |
| TN | 52 | 27 |
| FP | 33 | 21 |
| FN | 6 | 19 |
| Accuracy | 0.614 | 0.595 |
| Precision | 0.431 | 0.638 |
| Recall | 0.806 | 0.661 |
| Specificity | 0.612 | 0.563 |
| F1 Score | 0.562 | 0.649 |

Table 4 Accuracy matrix for the cyber security concern analysis

## Conclusion on Model:

* The model's intercept and both explanatory variables (age\_group and is\_student) are statistically significant, indicating that these variables collectively contribute to explaining the variation in the likelihood of expressing concern for security on internet.
* The negative coefficients for age\_group and is\_student suggest that, holding other variables constant, older age groups and being a student are associated with lower log-odds of expressing concern.
* The p-values for all coefficients are below conventional significance levels (e.g., 0.05), suggesting robust statistical evidence for their significance.
* In conclusion, this logistic regression model provides insights into the influence of age group and student status on the likelihood of expressing concern, offering a statistically significant understanding of the factors associated with the binary response variable.

## Random Forest Analysis to find fraud awareness.

## Purpose

We wanted to predict whether people are aware of fraud in digital payments using the response in our questioner.

## Variable Selection

|  |  |
| --- | --- |
| **Response Variable** | **Values** |
| fraud\_awareness | 1 for Yes , 0 for No |
| **Explanatory Variables** | **Values** |
| doing\_transaction | 1 for yes 0 for no |
| transaction\_method | Credit cards,ECS,IMPS,NEFT,Net banking ,RTGS,UPI |
| concerned | A little concerned,I know I should, but I am not concerned,Very much concerned |
| os\_update | Never, until compulsory,Occasionally,Rarely,Regularly |
| public\_network | No-never,Yes- mostly,Yes- sometimes |
| information\_security\_knowledge | Yes, No |
| data\_backup | Yes, No |
| data\_backup\_scheule | Occasionally,Rarely,Regularly |
| network\_security | Yes, No |
| lost\_money | Yes, No |
| two\_factor | Yes, No |
| gender | Female,Male,Prefer not to say |
| Age | Below 25,Between 26 to 40,Between 41 to 60 |
| Education | Graduation,Others,Post Graduation,Schooling |
| Occupation | Business,Housewife/househusband,Service,Student |
| income | 2 – 5 lakhs,Less than 2 lakhs,More than 10 up to 20 lakhs,More than 20 lakhs,More than 5 up to 10 lakhs |

Table 5 variable selection for the random forest method for fraud awareness

## Upscale data

* Used SMOTE for upscale data as our data has skewness toward awareness of fraud.

## Training testing division

* Splitted data into train and testing sets

## Model

Fitted the random forest method like below

|  |
| --- |
| explanatory\_variables <- c("doing\_transaction","transaction\_method  ","concerned","os\_update","  public\_network","information\_security\_knowledge  ","data\_backup","data\_backup\_scheule",  "network\_security",  "lost\_money",  "two\_factor",  "gender",  "Age","Education","Occupation","income")  formula <- as.formula(paste(response\_variable, "~", paste(explanatory\_variables, collapse = "+")))  # Train the random forest model  rf\_model <- randomForest(formula, data = train\_no\_missing\_rows,  mtry=4,  ntree=500) |

Code Snippet 2 random forest model for predicting fraud awareness.

## Validation of model

Model gives us accuracy of 100% on training and testing data, it seems to be overfit however since the data sample were limited , we conclude this could happen with small dataset and having categorical values

## Important Variables

A graph with numbers and text

Description automatically generated

Figure 19 important variables for the random forest analysis on fraud awareness

## Conclusion

From the analysis above, the random forest model can predict fraud awareness of the new observations and Two factor authentication, information security knowledge, network security, income are amongst the most significant variables influencing the awareness.

## Market Basket Analysis to find the rules for the people concerned.

## Purpose

To find the rules or combination of other factors that impact peoples’ concern about security on internet. To answer this question, we applied apriori algorithm to find set of rules among the data and filing rules where RHS is

Concern = Very much concerned

With this we can find other influencing factors that attributes to people’s concern on the security on internet.

## Method

Upscaled the data using caret library in R

Used minimum support as 20%

Used Threshold for confidence as 70%

## Derived Rules

We got many rules that were suggesting pattern of features in combinations, we filtered those rules where RHS was{Concern=Very much concerned}

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **lhs** | **rhs** | **support** | **confidence** | **lift** |
| {Age=Between 26 to 40} | => {Concern=Very much concerned} | 0.2211538 | 0.8214286 | 1.472906 |
| {Occupation=Service} | => {Concern=Very much concerned} | 0.3365385 | 0.7142857 | 1.280788 |
| {Age=Between 26 to 40, Occupation=Service} | => {Concern=Very much concerned} | 0.2211538 | 0.8214286 | 1.472906 |
| {Gender:=Male, Occupation=Service} | => {Concern=Very much concerned} | 0.2884615 | 0.7692308 | 1.379310 |

Table 6 Market Basket Rules for people very much concerned about security on internet

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Description automatically generated

Figure 20 rules for people very much concerned about security on internet

## Conclusion

People with following attributes are likely to have very much concerned about Cyber Security

* Age group 26 to 40
* Occupation : Service
* Gender : Male

## Market Basket Analysis to find factors behind lack of fraud awareness.

## Purpose

We wanted to predict who are the people that lacks fraud awareness, those are the people who can be knowing victim of fraud as they have less awareness that how prevalent is fraud in digital payments and fraud can happen to them.

For this we applied apriori algorithm to find the rules where fraud awareness was no. With this we wanted to find other influencing feature that contributes to lack of fraud awareness.

## Method for finding features for lack of fraud awareness.

Upscaled the data using caret library in R

Used minimum support as 20%

Used Threshold for confidence as 80%

## Derived Rules

We got many rules that were suggesting pattern of features in combinations, we filtered those rules where RHS was{ {fraud\_awareness=No}

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHS** | **RHS** | **Support** | **Confidence** | **lift** |
|  |  |  |  |  |
| {information\_security\_knowledge=No, | {fraud\_awareness=No} | 0.02884615 | 1 | 26 |
| data\_backup=No, |  |  |  |  |
| two\_factor=No, |  |  |  |  |
| Gender:=Female} |  |  |  |  |
|  |  |  |  |  |
| {public\_network=Yes, sometimes, | {fraud\_awareness=No} | 0.02884615 | 1 | 26 |
| data\_backup=No, |  |  |  |  |
| two\_factor=No, |  |  |  |  |
| Gender:=Female} |  |  |  |  |
|  |  |  |  |  |
| {transaction\_method=UPI, | {fraud\_awareness=No} | 0.02884615 | 1 | 26 |
| data\_backup=No, |  |  |  |  |
| two\_factor=No, |  |  |  |  |
| Gender:=Female} |  |  |  |  |
|  |  |  |  |  |
| {transaction\_method=UPI, | {fraud\_awareness=No} | 0.02884615 | 1 | 26 |
| information\_security\_knowledge=No, |  |  |  |  |
| data\_backup=No, |  |  |  |  |
| two\_factor=No, |  |  |  |  |
| Gender:=Female} |  |  |  |  |

Table 7 Market Basket Rules for lack of fraud awareness

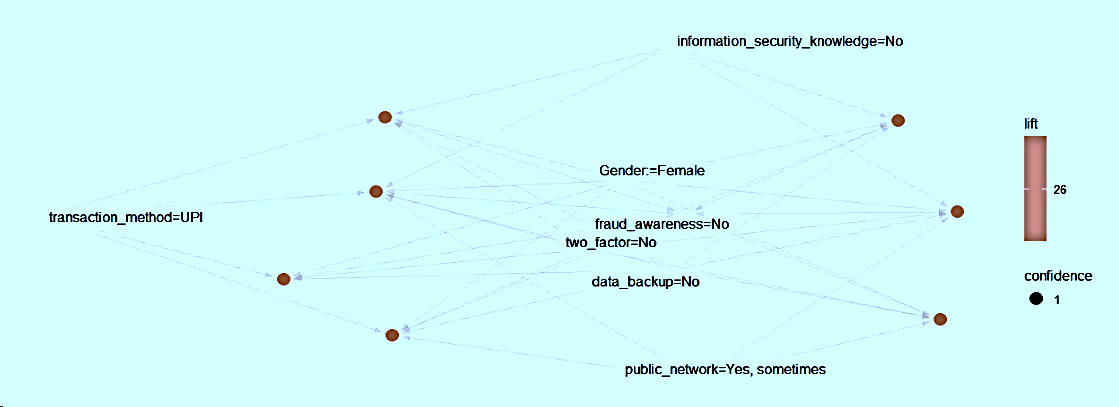


Figure 21 Rules for Lack of Fraud awareness.

## Conclusion

With above associate mining rules we could infer that data suggests people with following features lacks

Awareness about frauds

* + lack of information security knowledge
  + not doing data backup
  + not using two-factor authentication
  + and are female

## Market Basket Analysis to find online learning usage patterns.

## Purpose

To find the patten of usage of online learning platforms.

## Method for finding patterns in online learning.

* Data Corrections

Formatted data for the consistency as our data was open ended.

Manually updated values for consistency

e.g. youtube->YouTube

* Run the Apriori algorithm using excel workbook to find first level support
* Used minimum support as 5%
* Used Threshold for confidence as 75%
* Used Excel pivot for first level support

|  |  |
| --- | --- |
| **Platform** | **Count of Platform** |
| aakash | 1 |
| BnB | 1 |
| BYJU's | 13 |
| Coursera | 18 |
| DAMS | 4 |
| Emedicoz | 2 |
| Google Meet | 1 |
| Khan Academy | 1 |
| LinkedIn | 3 |
| Marrow | 15 |
| O'Reilly | 1 |
| Pluralsight | 1 |
| Prepladder | 2 |
| skillshare | 1 |
| teachable. | 1 |
| Udemy | 22 |
| Uworld | 1 |
| Webex | 1 |
| YouTube | 61 |
| (blank) |  |

Table 8 Market basket analysis for online learning platform usage - first level support

* Filtered the values not matching minimum support

|  |  |  |  |
| --- | --- | --- | --- |
| Platform | Count | Support Percentage | is greater than Min Support |
| aakash | 1 | 1% | FALSE |
| BnB | 1 | 1% | FALSE |
| BYJU's | 13 | 13% | TRUE |
| Coursera | 18 | 17% | TRUE |
| DAMS | 4 | 4% | FALSE |
| Emedicoz | 2 | 2% | FALSE |
| Google Meet | 1 | 1% | FALSE |
| Khan Academy | 1 | 1% | FALSE |
| LinkedIn | 3 | 3% | FALSE |
| Marrow | 15 | 14% | TRUE |
| O'Reilly | 1 | 1% | FALSE |
| Pluralsight | 1 | 1% | FALSE |
| Prepladder | 2 | 2% | FALSE |
| skillshare | 1 | 1% | FALSE |
| teachable. | 1 | 1% | FALSE |
| Udemy | 22 | 21% | TRUE |
| Uworld | 1 | 1% | FALSE |
| Webex | 1 | 1% | FALSE |
| YouTube | 61 | 59% | TRUE |

Table 9 Market Basket Analysis for online learning platform usage – First level support Filters

* Crated pairs from values matching minimum support in first level support and checked support of pairs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Pairs | | support | Support Percentage | is Support Percentage Greater Than Min Support |
| BYJU's | Coursera | 3 | 3% | FALSE |
| BYJU's | Marrow | 2 | 2% | FALSE |
| BYJU's | Udemy | 3 | 3% | FALSE |
| BYJU's | YouTube | 9 | 9% | TRUE |
| Coursera | Marrow | 1 | 1% | FALSE |
| Coursera | Udemy | 8 | 8% | TRUE |
| Coursera | YouTube | 16 | 15% | TRUE |
| Marrow | Udemy | 2 | 2% | FALSE |
| Marrow | YouTube | 10 | 10% | TRUE |
| Udemy | YouTube | 19 | 18% | TRUE |

Table 10 Market Basket Analysis for online learning platform usage - Support for pairs

* Crated triplets from values matching minimum support in pairs support and checked support of pairs

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Triplets | | | Support | Support Percentage | is Support > Min Support |
| BYJU's | Coursera | Marrow | 0 | 0% | FALSE |
| BYJU's | Marrow | Udemy | 0 | 0% | FALSE |
| BYJU's | Udemy | YouTube | 2 | 2% | FALSE |
| Coursera | Marrow | Udemy | 0 | 0% | FALSE |
| Coursera | Udemy | YouTube | 7 | 7% | TRUE |
| Marrow | Udemy | YouTube | 2 | 2% | FALSE |

Table 11 Market Basket Analysis for online learning platform usage - Support for triplets

* Created association mining rules from the triplets

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| A | |  | B | |  | Support Of A U B | Support of A | Confidence Support Of A U B/Support Of A | Confidence Greater than Min Confidence? |
| LHS |  |  | RHS |  |  |  |  |  |  |
| Coursera | YouTube | -> | Udemy |  |  | 7 | 16 | 44% | FALSE |
| Coursera | Udemy | -> | YouTube |  |  | 7 | 8 | 88% | TRUE |
| YouTube | Udemy | -> | Coursera |  |  | 7 | 19 | 37% | FALSE |
|  | Coursera | -> | Udemy | YouTube |  | 7 | 18 | 39% | FALSE |
|  | Udemy | -> | Coursera | YouTube |  | 7 | 22 | 32% | FALSE |
|  | YouTube | -> | Coursera | Udemy |  | 7 | 61 | 11% | FALSE |

Table 12 Market Basket Analysis for online learning platform usage - Rules

## Conclusion

* With above associate mining rules we could infer that data suggests people using coursera, YouTube also uses Udemy.
* With more such rules on different features can give valuable insight into the usage patterns of digital platforms, e-services

## Random forest analysis to find important factors contributing to probability of money loss in fraud.

## Purpose

To find important features that can be used for further analysis to predict money loss behaviour

## Data Upscaling - SMOTE

Using Random forest machine learning technique, we want to find out most important features for the response variable money lost during online transaction.

Raw data structure   
Total Variables: 43  
Response variable: money lost during online transaction(count of people who lost money during online transaction)  
Total no of observations: 97

As figure 11 reveals that data is imbalanced. Using SMOTE technique, data is balanced. As majority of responses fall in “ Yes” category where in Yes indicates person has lost money during online transaction while No indicates not lose money during online transaction.

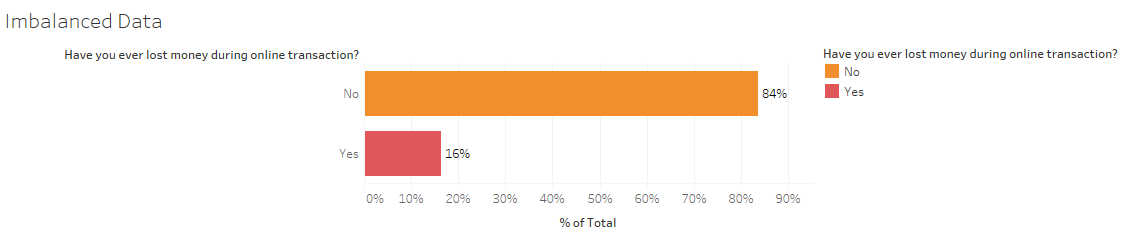


Figure 22 Imbalanced data of response variable money lost during online transaction

## Data Partitioning

Now, we divide data set into two categories.

|  |  |
| --- | --- |
| Particular | % of total data |
| Training Data | 80% |
| Testing Data | 20% |

Table 13 Data Partitioning for Random forest model

## RF Model building

To build effective Random forest model, we have used param\_grid function to fine tune hyper parameters. Below are opted value of hyper parameters.

No of estimators= 100  
Minimum smaple split=2  
Minimum sample leaf=2  
Maximum features=6(square root of total features)  
Maximum depth=30

## RF model Performance

Using above hyper parameters , model is now applied to test data to check the various performance metric. Below table represents the performance matrix.

|  |  |  |
| --- | --- | --- |
| Particular | Training Data | Testing Data |
| Accuracy | 100% | 91% |
| F1 Score | 90 | 91 |
| Out-of-bag error rate | NA | 15.5% |

Table 14 Random forest model performance metrics

## Important variable features selection

RF model is not interpretative model but it gives important features related to response variable. Using this unique feature of the model we will extract important variable from the plot of Variable importance plot. Below figure is variable importance plot where in there are total 41 features are plotted in descending order of importance.

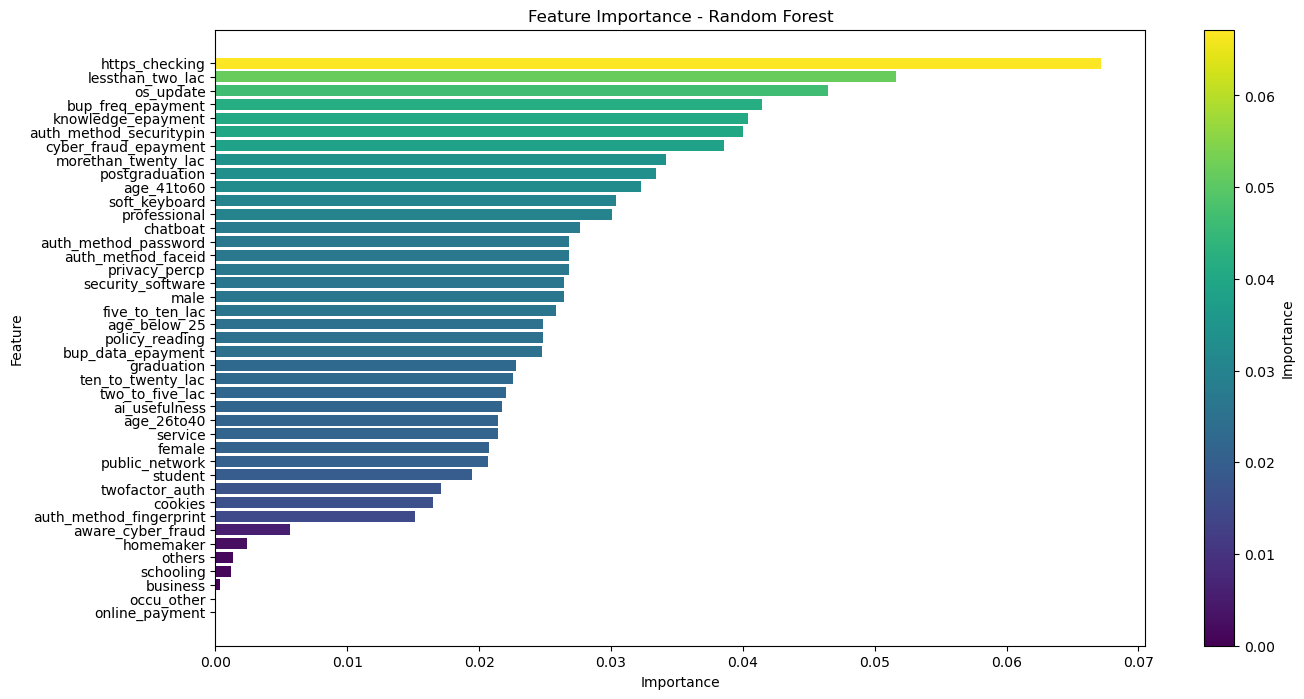
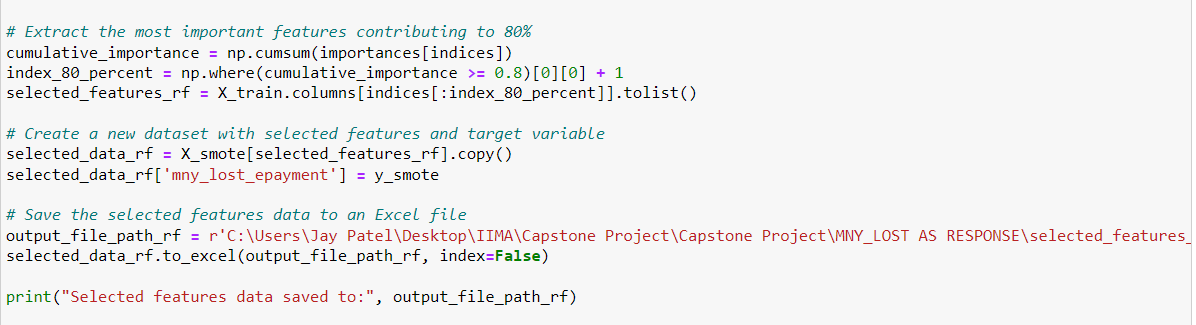


Figure 23 VARIABLE IMPORTANCE PLOT FOR RESPONSE MONEY LOST

## Extracting the most important features- Pareto Rule

As we can see in figure 12, there are 41 features in plot, hence to reduce the no of features to work further we now, use Pareto rule to extract the features whose total contribution in importance is 80%  
After application we are left with total 25 features from 41 features. The code snip shot of Pareto rule is shown in figure 13.



Code Snippet 3 Pareto rule application to get 80% contributed features from variable importance plot

|  |  |
| --- | --- |
| Total features (Variable importance plot) | Extracted features after Pareto rule application |
| 41 | 26 |

Table 15 Extraction of features using Pareto rule

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| https checking | Security method: Pin | Use of soft keyboard | Privacy perception | Age< 25 Years | Annual Income: 2-5 lakhs |
| Annual income < 2 lakhs | Face any cyber fraud | Working Professional | Usage of security software | Reading Policy? | - |
| Regular OS update | Annual income > 20 lakhs | Usage of chatbot | Male | Back up data | - |
| Back up frequency of data | Postgraduate | Security method: Password | Female | Graduate | - |
| Knowledge of e payment | Age 41 - 60 | Security method: Face id | Annual income: 5-10 lakhs | Annual income: 10-20 lakhs | - |

Table 16 Extracted features for further analysis.

## Extracted features - As Raw data for next analysis

Selected 26 features after Pareto rule application , we have used these data set along with money lost as our response for next Logistic regression model building.

## Logistic regression to find probability of money loss in fraud.

## Purpose

To find the variable that could help to reveal the probability of money loss in fraud and prevent cyber frauds. This model not only helps in classifying the categories of people who lost money but inherently it also reveals the behavioral pattern of those who are prone to loose money or vice a versa.  
We , now, use selected features data from the rf model and Pareto application to work further.

## Data Partitioning

|  |  |
| --- | --- |
| Particular | % of total data |
| Training Data | 70% |
| Validating Data | 15% |
| Testing Data | 15% |

Table 17 Data splitting for Logistic Regression Model

## Building Logistic Regression Model

Using Training data , we get final model of logistic regression which further tested on test data.   
On train data, we build initial logistic regression model by applying Backward elimination method we will get the most significant variables which are the prime driving variables to decide/predict the money lost (fraud).

## Backward Elimination method- Logistic Regression

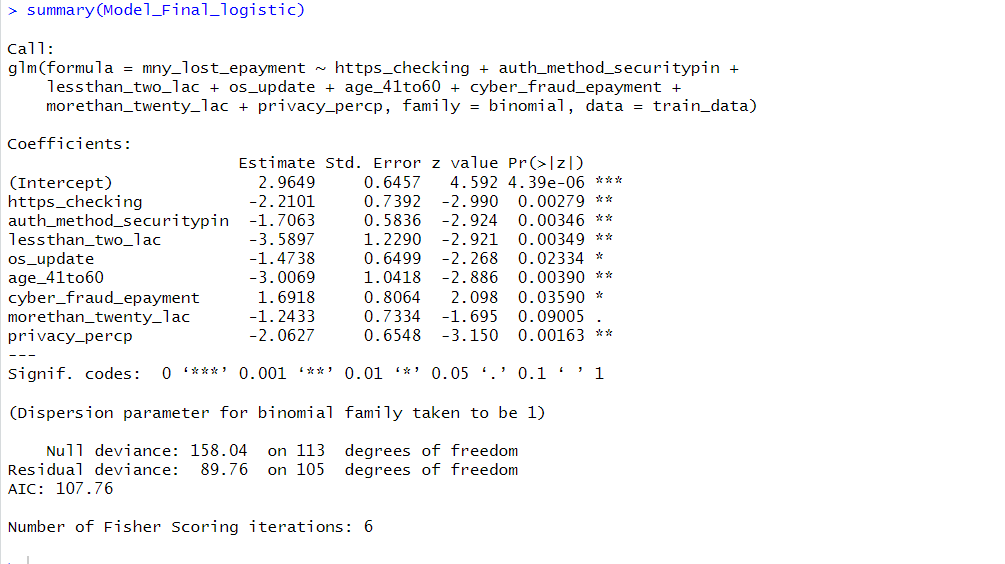
On testing data,now, we use backward elimination method and threshold value for cut off are as mentioned below in table

|  |  |
| --- | --- |
| Particular | Cut-off value |
| VIF | < 3 (less than 3) |
| P value | < 0.1 (less than 0.1) |

Table 18 Backward elimination cut off value threshold

## Most Significant variables- Logistic Regression

Figure below is summary of LR model on validation data, which gives important insights on money fraud during online transaction.



Code Snippet 4 LR model summary (test data)

Now, we have clear insights for those class of people who have not lost money during online  
transaction. Out of 8 significant variables, 6 variables are in negative association with response money lost. Now,let us discuss about some insights we get from above summary.

## Important key notes from- Logistic Regression model.

Below table tells the probability of each class of people who are having very less likely hood of losing money during online transaction as are having negative association with response.

|  |  |
| --- | --- |
| Class of Person | Probability(%) of losing Money during online transaction |
| Age bracket of 41 to 60 | 4.7% |
| Annual Income < 2 Lakhs | 2.69% |

Table 19 Least likelihood of losing money during online transaction

(keeping other variable constant while calculating each class probability)

It is very interesting to note that those who are having annual income less than 2 lakh are very least prone to money fraud during online transaction.

If we talk about age bracket, then surprisingly, people of age 41 to 60 during online transaction are having very less probability to loose money.

Table no 14 shares , the rest of class of people probability of not loosing money.

|  |  |
| --- | --- |
| Class of Person | Probability(%) of losing Money during online transaction |
| https checking (authentic web address) | 9.8% |
| Usage of Security method: Pin | 15.36% |
| Regular OS update | 18.64% |
| Annual income > 20 lakhs | 22.39% |

Table 20 Probability of losing money during online transaction

(keeping other variable constant while calculating each class probability)

There are two more variables which are positively associated with response money lost and probability of loosing money are shown in below table no 15.

|  |  |
| --- | --- |
| Class of Person | Probability(%) of losing Money during online transaction |
| Victim of cyber fraud(other than monetary fraud) | 84.45% |
| Privacy perception (who believes sharing data to chatgpt and chat-boat hamper their privacy) | 11.28% |

Table 21 Probability of losing money during online transaction

## Validating Predictive Model

Now, we use validation data to get optimal threshold to make model more accurate and effective.

We have chosen F1 score as priority to get optimal threshold value. We have also considered Area under curve value of ROC plot.

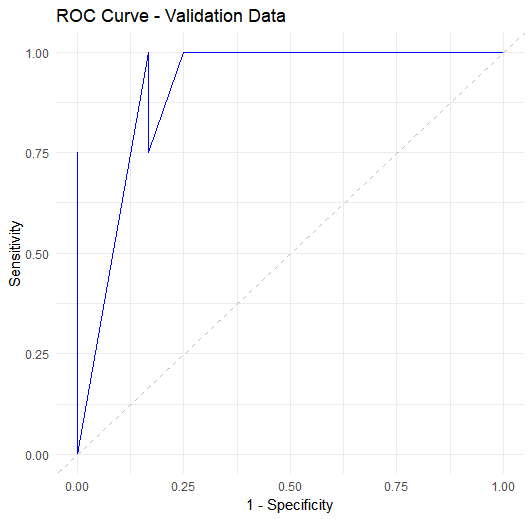


Figure 24 ROC Curve

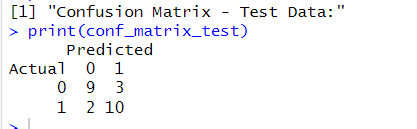
Figure 15 is ROC curve and the value of AUC is 0.95 , which is reasonably high to continue further with this model. While keeping F1 score high as priority, the threshold value obtained is mentioned below in table.

|  |  |
| --- | --- |
| Threshold Value obtained | 0.23 |
| Area Under Curve | 0.96 |

Table 22 Optimal threshold value

## Testing Predictive ability of Model

It’s time to test the model on testing data, here we will have mainly testing performance to check the predictive ability of model. Various performance measures are mentioned in table below. For better understanding of the model performance we need to compare it with train data performance metrics as well. Related to measures , confusion matrix is also shown in figure no 16.



Code Snippet 5 Confusion matrix(test data)

|  |  |  |
| --- | --- | --- |
| **Performance Measures** | Training Data | Testing Data |
| Accuracy | 87.7% | 79.16% |
| Precision | 84.12% | 76.92% |
| Recall | 92.98% | 83.33% |
| F1 Score | 88.3 | 80.0 |

Table 23 Performance Measures of Training and Testing Data

Note: All the analysis codes are checked into (Rajiv, 2023)for easy reference, version control and collaboration amongst the team

# Results

Cyber Security Concerns:

* + Logistic Regression: Age group and student status influence concerns.
  + Random Forest: Successfully predicts cyber fraud awareness.
  + Apriori Rules: Higher concern in age 26 to 40, service occupation, and male gender.

Fraud Awareness:

* + Apriori Rules: Lack of awareness linked to no information security knowledge, no data backup, no two-factor authentication, and female gender.

Fraud Loss Prediction:

* + Random Forest: Non-loss characteristics include HTTPS checking, security pin authorization, income less than two lac, regular OS updates, age 41 to 60, income more than twenty lac, and privacy concern.
  + Logistic Regression: Effective in predicting money loss.

# Conclusion

These findings collectively emphasize the intricate nature of cybersecurity concerns, fraud awareness, and the prediction of financial losses in online transactions. The influence of demographic factors, information security practices, and individual characteristics contributes to a nuanced understanding of the challenges and opportunities in promoting secure digital transactions. Strategies to enhance cybersecurity should consider targeted measures based on age, occupation, gender, and awareness levels to effectively address concerns and mitigate the risk of financial loss.

# Recommendations

## Concentrated Ad Campaigns

* Leverage the insights gained from the project study to design and implement concentrated advertising campaigns. Tailor these campaigns to address specific concerns identified in different demographic segments, such as age groups, occupations, and gender.
* Highlight the security features and benefits of digital payment systems, emphasizing the measures taken to address the concerns raised by various user groups.

## Develop and Market Cybersecurity Products

* Use the findings from the study to inform the development of cybersecurity products that specifically target the identified risk factors. Consider creating user-friendly interfaces that align with the preferences and concerns of different demographic groups.
* Market these cybersecurity products as essential tools for securing online transactions, with a focus on addressing the vulnerabilities highlighted in the study.

## Establish Targeted Educational Programs

* Develop targeted educational programs based on the insights and inferences obtained from the project study. Tailor these programs to address the specific awareness gaps identified in different demographic categories, such as age, gender, and knowledge levels.
* Collaborate with educational institutions, businesses, and community organizations to implement these programs, ensuring widespread access to cybersecurity education.

## Customized Communication Strategies:

* Implement customized communication strategies for different audience segments, taking into account the preferences and concerns revealed in the study. This could include designing communication materials that resonate with specific age groups, occupations, and genders.
* Utilize multiple channels, including social media, community events, and targeted online platforms, to disseminate information about cybersecurity measures and promote safe digital practices.

By implementing these recommendations, organizations and policymakers can proactively address cybersecurity concerns, enhance awareness, and contribute to the promotion of secure digital transactions. The customization of strategies based on demographic factors ensures a more targeted and effective approach in reaching and influencing diverse user groups.

# References

*Economic Survey 2023*. (2023, January 31). Retrieved from moneycontrol.com: https://www.moneycontrol.com/news/business/economic-survey-2023-upi-accounted-for-52-of-indias-total-digital-transactions-in-fy22-9970741.html

*IIM Library*. (2023, 11 01). Retrieved from IIM Library: https://library.iima.ac.in/

Joshi, C. (2023, 11 15). *Google Form*. Retrieved from Google Form: https://forms.gle/eidJ1KNXuTGur3NB9

Kegelmeyer, N. C. (2002). SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intellegence Research*, 328-347.

*Managing imbalance Data Set with SMOTE in Pythone*. (2020, March 11). Retrieved from oralytics.com: https://oralytics.com/2019/07/01/managing-imbalanced-data-sets-with-smote-in-python/

Rajiv, C. H. (2023, 11 11). *Github*. Retrieved from Github: https://github.com/rajivtrivedi/epababl05