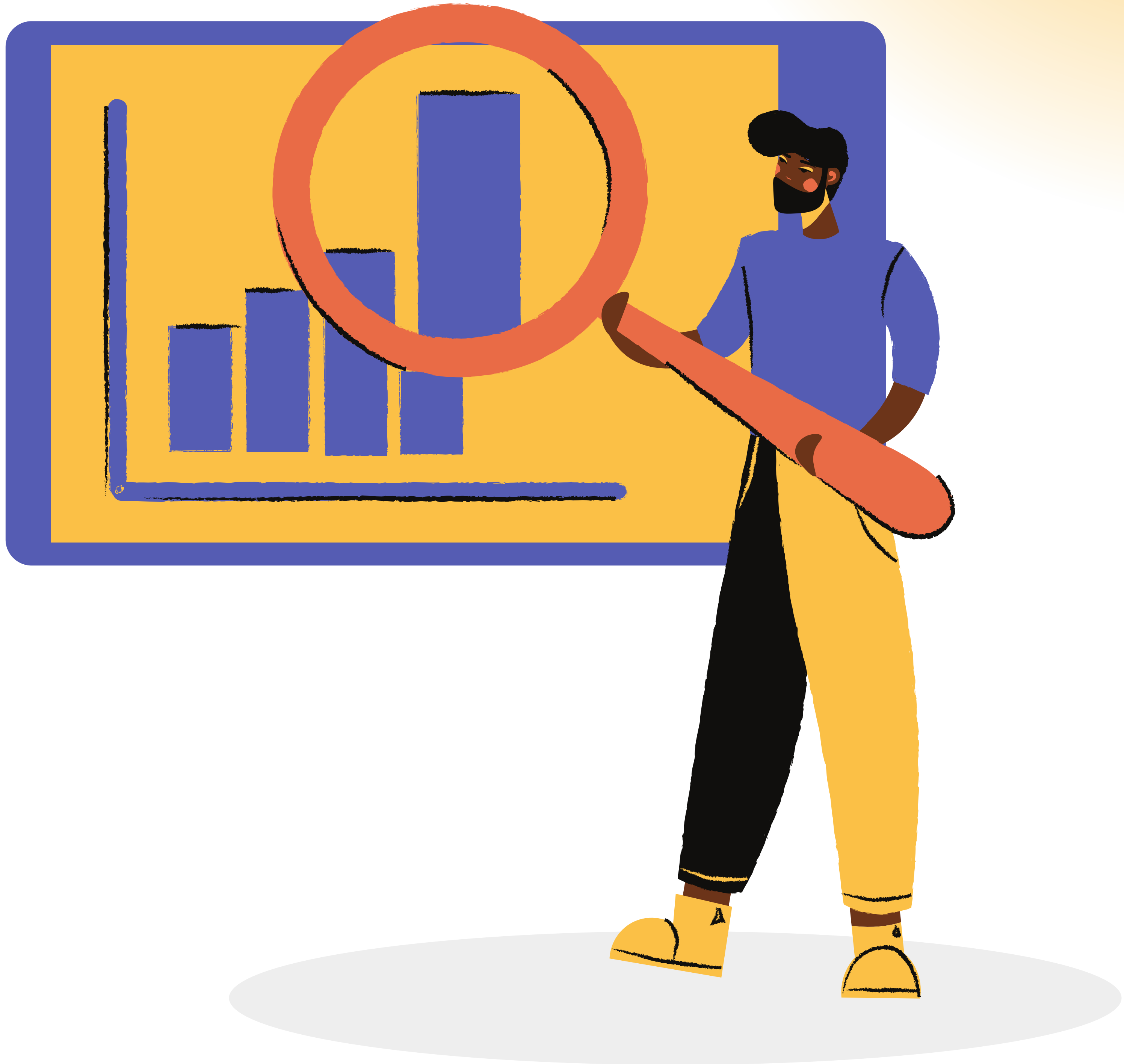
Differentiating Users of E-Payments

Looking into factors that categorizes users into heavy or light users to increase the usage of E-Payments

By Group L1, Section 2,
Manjul Mayank Tripathi (21F233),
M Manohar Prabhu (21F234),
Nishu Choudhary (21F237),
Saurabh Singh (21F252),
Sourish Atorthy (21F258)

Under the Guidance of,
Prof. Tathagata Ghosh



What are E-Payments?

Any payment made through the internet for products or services

Why this Research?

- Trying to understand what variables determines a user is a heavy or light user of E-Payments.

- On correctly understanding the factors, focus can be correctly given to increase usage among the light users especially.

Research Design

Descriptive Research Design

Defining the Information Needed

NEXT

Secondary Data Analysis

NEXT

In-Depth Interviews (Qualitative Data)

NEXT

Google Forms (Quantitative Data)

NEXT

Research Design

Descriptive Research Design

- Ratio Scale & 5-Point Likert Scale Items (Scaling Technique)
- Questionnaire Design
- Judgement Sampling (Sampling Technique)
- Discriminant Analysis (Methodology)

List of Variables

Type of Users

1 - Light User

2 - Heavy User

Dependent Variable

Age

Monthly Transactions

Monthly Errors

Security

Promotions & Discounts

App Interface

Reduction of Carrying Cash

Ready Availability

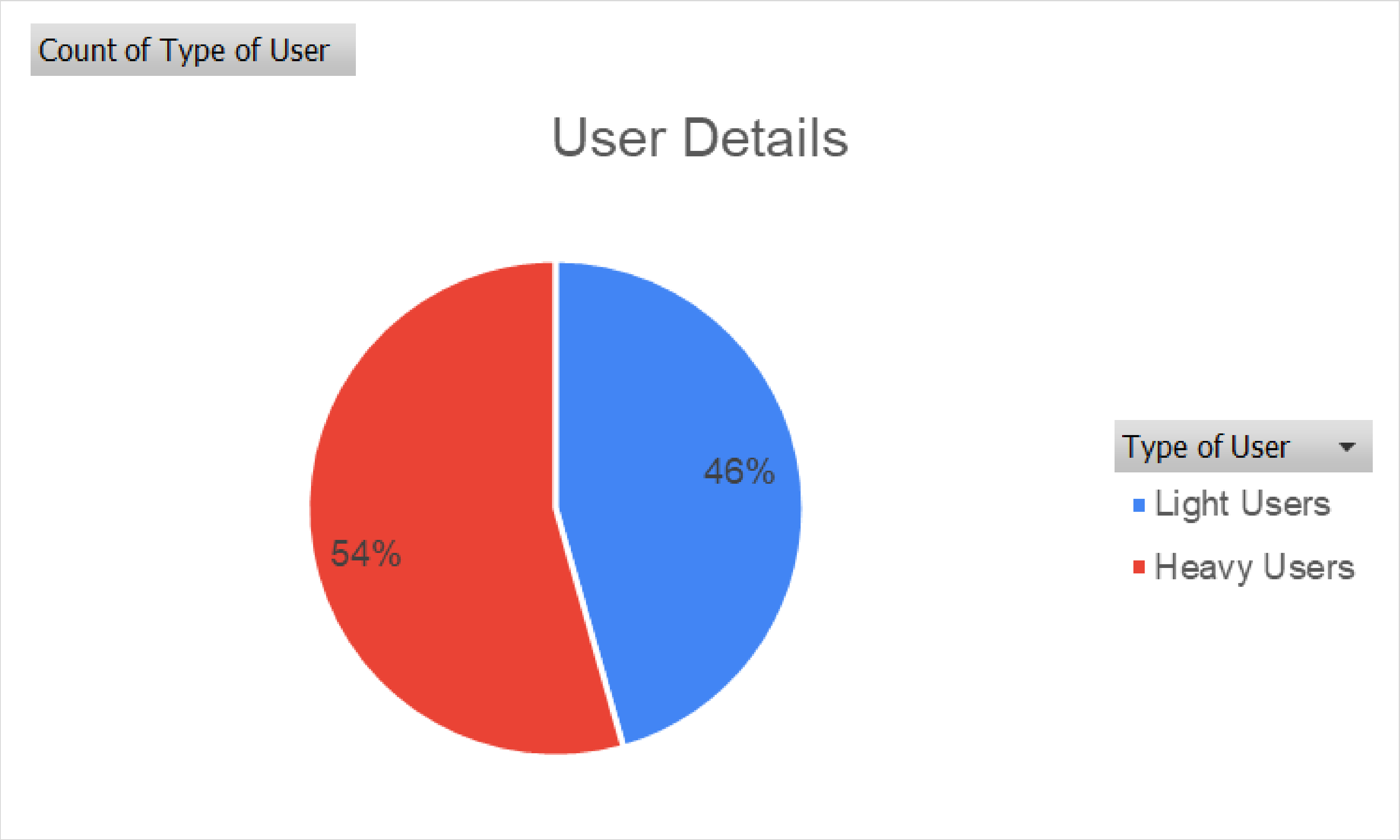
Reduction of Human Interaction

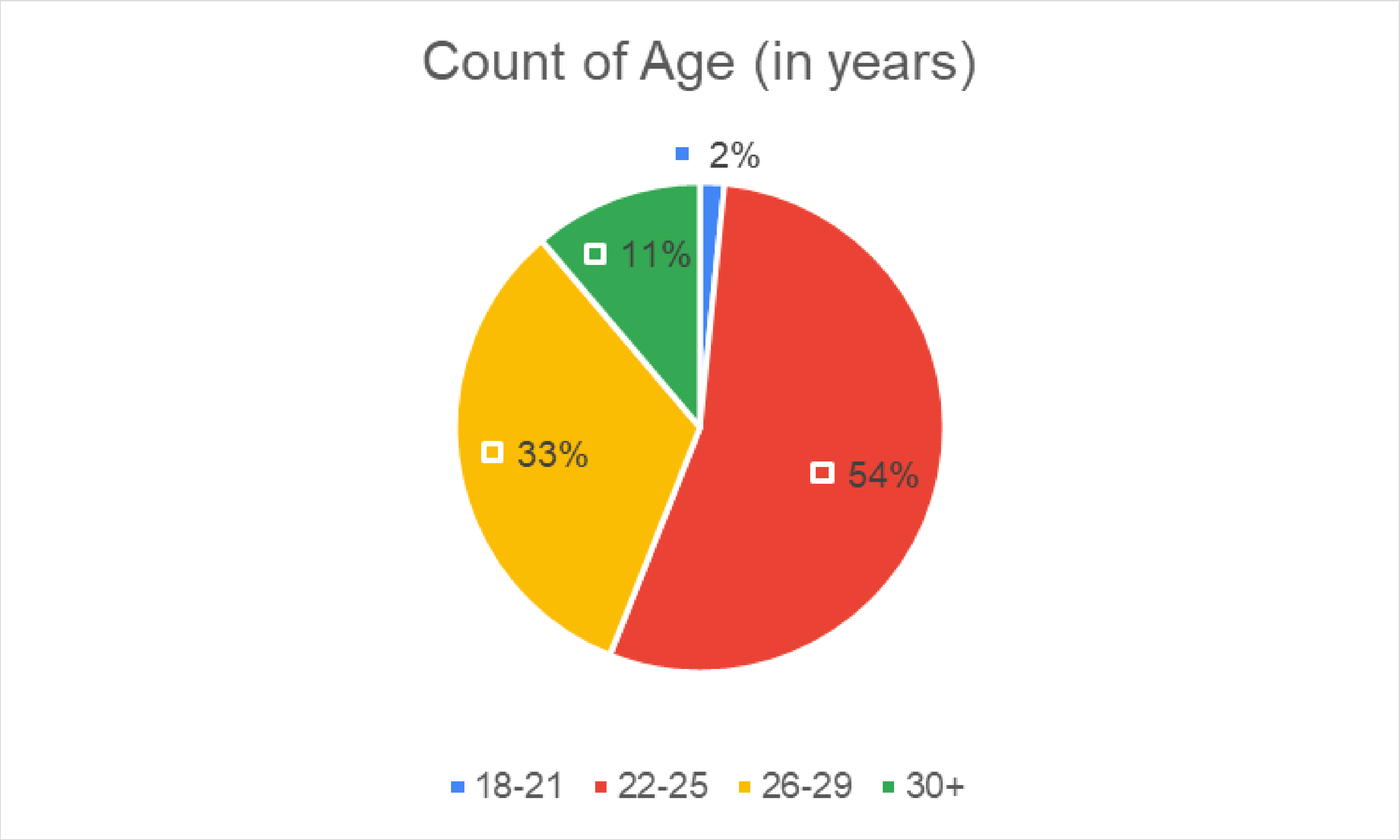
Tech-Savviness

Independent Variables

Type of Users & Age Division

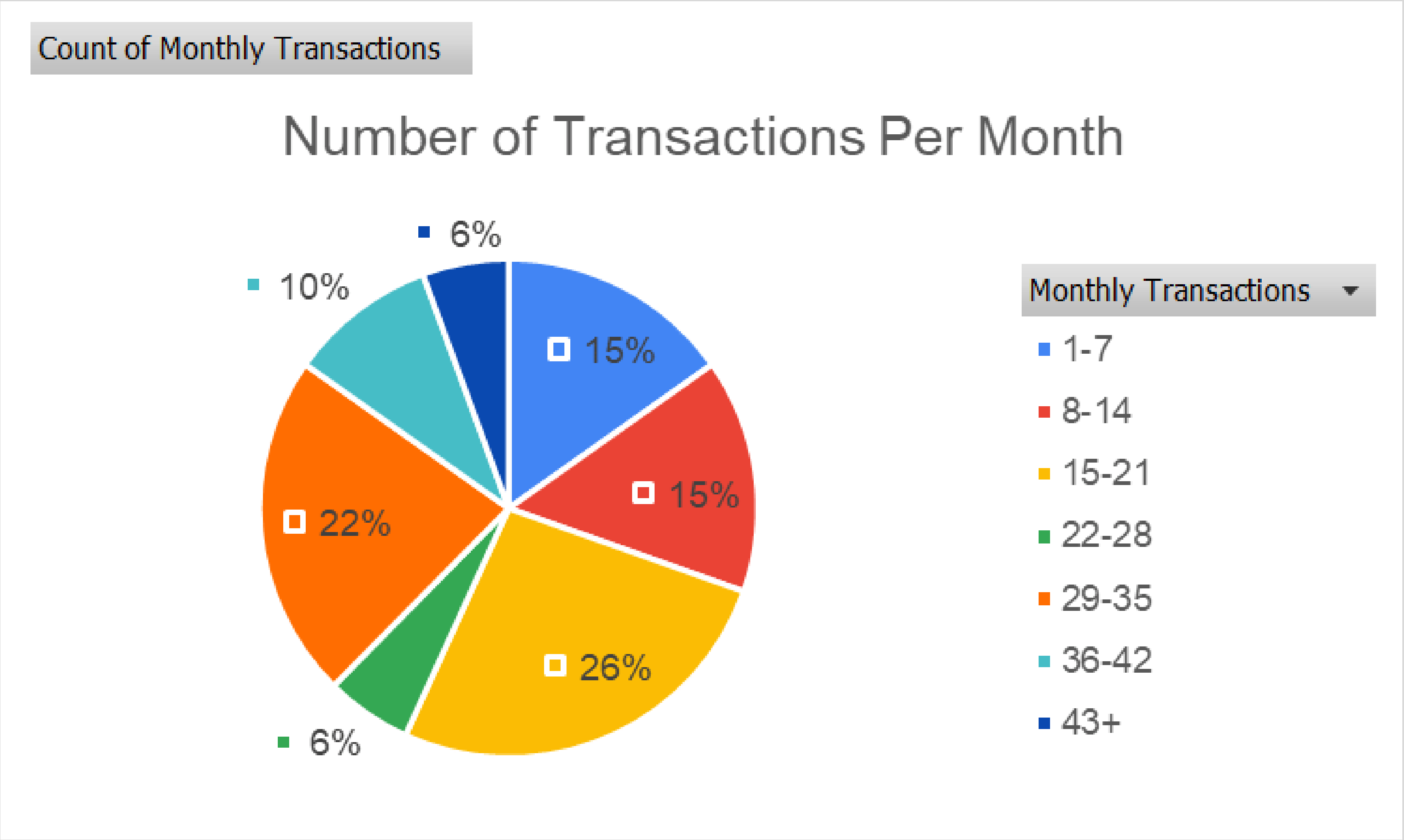
Data Analysis : Sample Profile

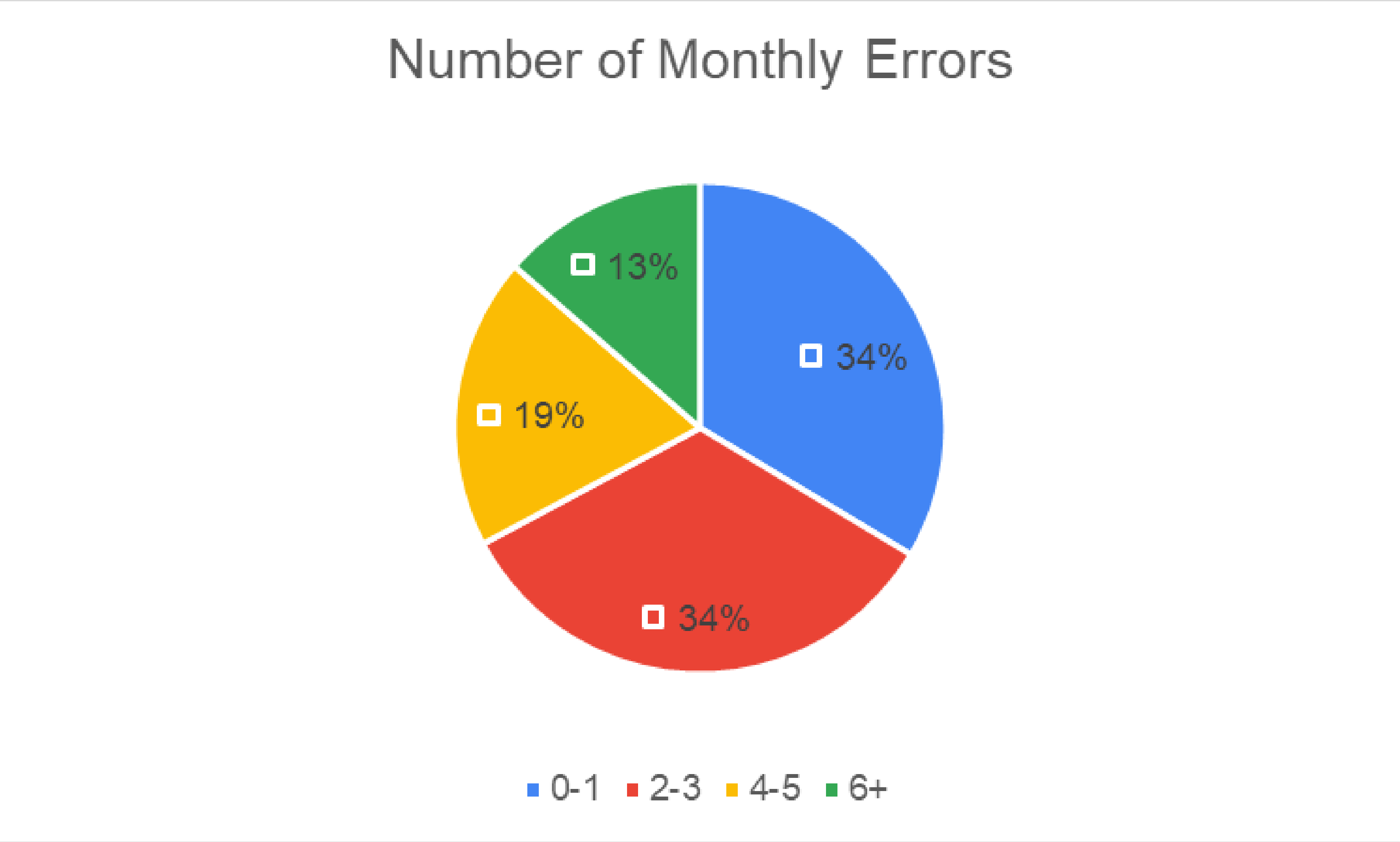




Monthly Transactions & Errors

Data Analysis : Sample Profile





Discriminant Analysis

Data Analysis : Methodology

1. **Discriminant Model**:

Type of E-Payment User (D_0) = b_0 + b_1.(Age) + b_2.(Monthly Transactions) + b_3.(Monthly Errors) + b_4.(Security) + b_5.(Application Interface) + b_6.(Reduction of Carrying Cash)+ b_7.(Promotions & Discounts) + b_8.(Ready Availability) + b_9.(Reduction of Direct Human Interaction) + b_{10}.(Tech-Savviness) + Ɛ

2. **Model Hypothesis & Wilks' Lambda Table**:

H_0: The discriminant model is not statistically significant
H_a: The discriminant model is statistically significant

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.345	125.601	10	.000

So, we reject the null hypothesis as Significane is less than 0.05

Discriminant Analysis

Data Analysis : Methodology

3. Group Statistics Table:

1: Light User

2: Heavy User

Group Statistics

Type of User		Mean	Std. Deviation	Valid N (listwise) Unweighted	Valid N (listwise) Weighted
1	Age (in years)	26.47	7.758	57	57.000
	Monthly Transactions	10.68	6.814	57	57.000
	Monthly Errors	2.12	3.088	57	57.000
	Security	4.95	.225	57	57.000
	Application Interface	4.46	.888	57	57.000
	Reduction of Carrying Cash	4.37	1.011	57	57.000
	Promotions & Discounts	2.81	1.469	57	57.000
	Ready Availability	3.91	.808	57	57.000
	Reduction of Direct Human Interaction	3.58	1.238	57	57.000
	Tech-Sawiness	3.19	1.355	57	57.000
2	Age (in years)	25.87	3.350	68	68.000
	Monthly Transactions	31.03	9.277	68	68.000
	Monthly Errors	3.91	3.222	68	68.000
	Security	4.88	.406	68	68.000
	Application Interface	4.69	.553	68	68.000
	Reduction of Carrying Cash	4.79	.442	68	68.000
	Promotions & Discounts	2.76	1.467	68	68.000
	Ready Availability	4.62	.692	68	68.000
	Reduction of Direct Human Interaction	3.46	1.215	68	68.000
	Tech-Sawiness	3.75	.968	68	68.000
Total	Age (in years)	26.14	5.774	125	125.000
	Monthly Transactions	21.75	13.076	125	125.000
	Monthly Errors	3.10	3.274	125	125.000
	Security	4.91	.336	125	125.000
	Application Interface	4.58	.732	125	125.000
	Reduction of Carrying Cash	4.60	.783	125	125.000
	Promotions & Discounts	2.78	1.462	125	125.000
	Ready Availability	4.30	.823	125	125.000
	Reduction of Direct Human Interaction	3.51	1.222	125	125.000
	Tech-Sawiness	3.50	1.189	125	125.000

After a quick visual inspection, we can see that there is a good difference in the means of monthly transactions and errors, and the ready availability variables. So, they might be good variables to determine the difference among users. Later, in another table we will validate this assumption.

Discriminant Analysis

Data Analysis : Methodology

4. Independent Variables Hypothesis:

H_{10}: Mean of the **Age** doesn't vary much between the two groups
H_{1a}: Mean of the **Age** vary between the two groups

H_{20}: Mean of the **Monthly Transactions** doesn't vary much between the two groups
H_{2a}: Mean of the **Monthly Transactions** vary between the two groups

H_{30}: Mean of the **Monthly Errors** doesn't vary much between the two groups
H_{3a}: Mean of the **Monthly Errors** vary between the two groups

H_{40}: Mean of the **Importance to Security** doesn't vary much between the two groups
H_{4a}: Mean of the **Importance to Security** vary much between the two groups

H_{50}: Mean of the **Importance to Application Interface** doesn't vary much between the two groups
H_{5a}: Mean of the **Importance to Application Interface** vary between the two groups

H_{60}: Mean of the **Importance to Reduction of Carrying Cash** doesn't vary much between the two groups
H_{6a}: Mean of the **Importance to Reduction of Carrying Cash** vary between the two groups

H_{70}: Mean of the **Importance to Promotions & Discounts** doesn't vary much between the two groups
H_{7a}: Mean of the **Importance to Promotions & Discounts** vary between the two groups

H_{80}: Mean of the **Importance to Ready Availability** doesn't vary much between the two groups
H_{8a}: Mean of the **Importance to Ready Availability** vary between the two groups

H_{90}: Mean of the **Importance to Reduction of Direct Human Interaction** doesn't vary much between the two groups
H_{9a}: Mean of the **Importance to Reduction of Direct Human Interaction** vary between the two groups

H_{100}: Mean of the **Importance to Tech-Savviness** doesn't vary much between the two groups
H_{10a}: Mean of the **Importance to Tech-Savviness** vary between the two groups

Discriminant Analysis

Data Analysis : Methodology

5. Test of Equality of Group Means Table:

Tests of Equality of Group Means							
	Wilks' Lambda	F	df1	df2	Sig.	Result	Rank (As Per Wilks' Lambda)
Age (in years)	.997	.340	1	123	.561	Do Not Reject Null Hypothesis	8
Monthly Transactions	.395	188.700	1	123	.000	Reject Null Hypothesis	1
Monthly Errors	.925	9.927	1	123	.002	Reject Null Hypothesis	3
Security	.991	1.160	1	123	.284	Do Not Reject Null Hypothesis	7
Application Interface	.974	3.259	1	123	.073	Do Not Reject Null Hypothesis	6
Reduction of Carrying Cash	.926	9.820	1	123	.002	Reject Null Hypothesis	4
Promotions & Discounts	1.000	.026	1	123	.873	Do Not Reject Null Hypothesis	10
Ready Availability	.816	27.654	1	123	.000	Reject Null Hypothesis	2
Reduction of Direct Human Interaction	.997	.313	1	123	.577	Do Not Reject Null Hypothesis	9
Tech-Sawiness	.945	7.145	1	123	.009	Reject Null Hypothesis	5

So, from this table we can say Monthly Transactions, Monthly Errors, Reduction of Carrying Cash, Ready Availability & Tech-Savviness are the discriminating variables amongst the two groups of users. Wilks' Lambda range between 0 to 1 & lower the value, the higher is the differentiating power of the variable. So, Monthly Transactions differentiate the groups the most followed by ready availability, month errors and so forth.

Discriminant Analysis

Data Analysis : Methodology

6. Eigen Values Table:

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.899[a]	100.0	100.0	.809

a. First 1 canonical discriminant functions were used in the analysis.

The correlation between the dependent and independent variables is 0.809. Square of that is 0.6545. So, 65.45% of the variance in usage of e-payments is explained by the discriminant model.

Eigen value is the ratio of between group variance and within group variance. The higher the value of Eigen value the better is the model. But we cannot say anything with this as we would need another model's eigen value to actually compare.

Discriminant Analysis

Data Analysis : Methodology

7. Structure Matrix:

Structure Matrix

	Function
	1
Monthly Transactions	.899
Ready Availability	.344
Monthly Errors	.206
Reduction of Carrying Cash	.205
Tech-Sawiness	.175
Application Interface	.118
Security	-.070
Age (in years)	-.038
Reduction of Direct Human Interaction	-.037
Promotions & Discounts	-.011

Structure matrix ranks the variables for their importance in differentiating the users similarly like Wilks' Lambda. But here, higher the structure loadings are, the more important the variable is. So, the Wilks' Lambda table and this should ideally converge, and we can see it is actually converging.

Discriminant Analysis

Data Analysis : Methodology

8. Canonical Discriminant Function Coefficients:

Canonical Discriminant Function Coefficients

	Function
	1
Age (in years)	-.010
Monthly Transactions	.119
Monthly Errors	-.074
Security	-.749
Application Interface	.014
Reduction of Carrying Cash	.217
Promotions & Discounts	.009
Ready Availability	.365
Reduction of Direct Human Interaction	-.196
Tech-Sawiness	.057
(Constant)	-.589

So, the model becomes,

Type of E-Payment User (D_0) = −0.589 − 0.010(Age) + 0.119(Monthly Transactions) − 0.074(Monthly Errors) − 0.749(Security) + 0.014(Application Interface) + 0.217(Reduction of Carrying Cash) + 0.009(Promotions & Discounts) + 0.365(Ready Availability) – 0.196(Reduction of Direct Human Interaction) + 0.057(Tech-Savviness)

9. Functions at Group Centroid:

Functions at Group Centroids

Type of User	Function
	1
1	-1.493
2	1.252

If we multiple each value with the coefficients and add the constant, we will get the z-score of each data point. Taking the average of all z-scores of a particular group will give the group centroid. With the group centroid we can calculate the cutting score. The cutting score is -0.2413.

Now if a new data point comes, we will calculate the z-score of this user and if it is greater than -0.2413 then it belongs to Group 2 and vice versa.

Discriminant Analysis

Data Analysis : Methodology

10. Classification Statistics:

Classification Results[a]

		Type of User	Predicted Group Membership 1	Predicted Group Membership 2	Total
Original	Count	1	53	4	57
		2	5	63	68
	%	1	93.0	7.0	100.0
		2	7.4	92.6	100.0

a. 92.8% of original grouped cases correctly classified.

SPSS calculates all the discriminant z-scores and re-evaluates the grouping. Here, it found that as per our model 58 should be light users and 67 heavy users and our model is wrongly classifying 9 users. So, our hit ratio is ((53/57)+(63/68))/2 = 92.8%. Evidently, our miss ratio will be 100-92.8 = 7.2%

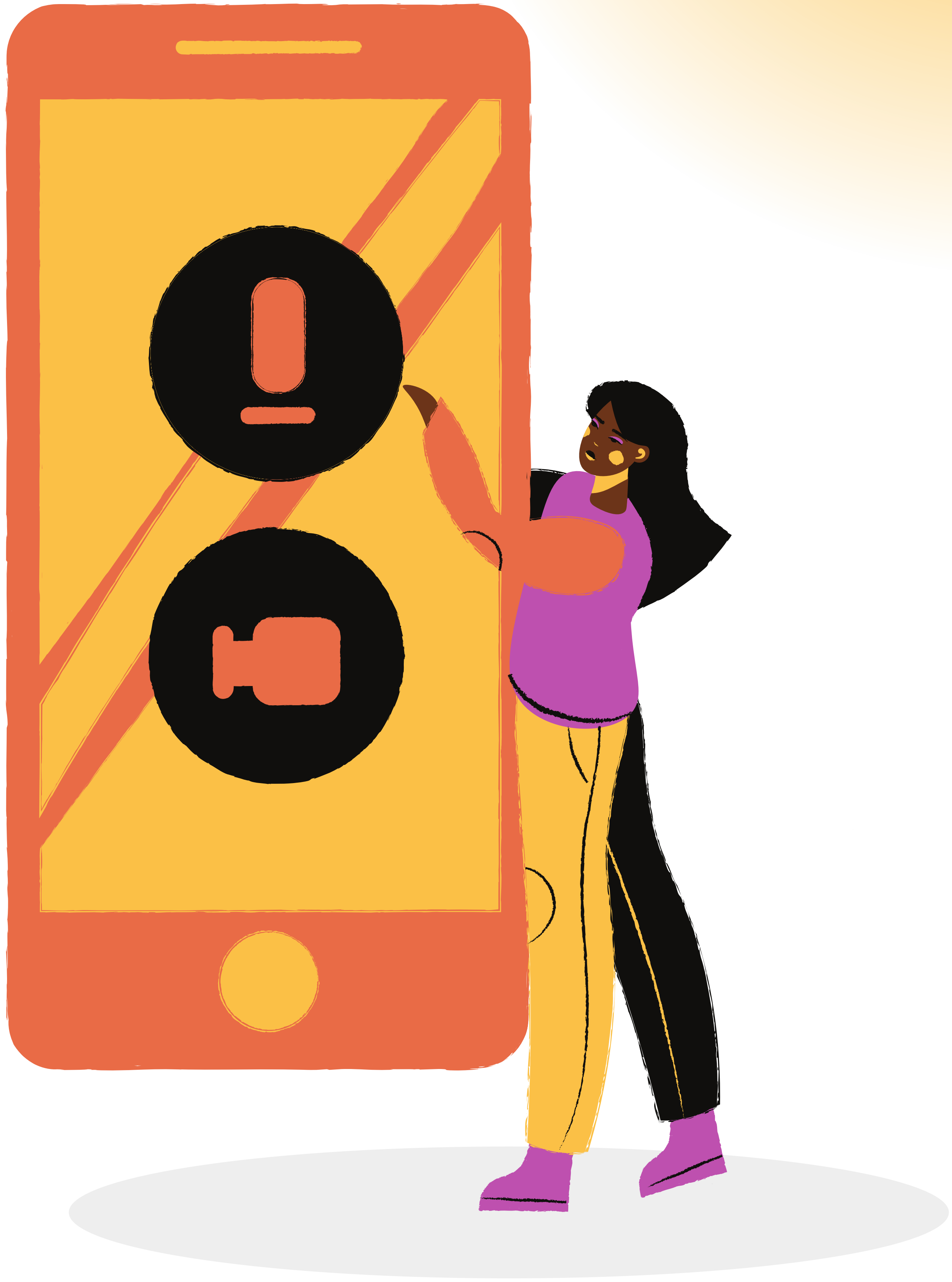
Managerial Implications & Recommendations

So, from the research we understand,

- Users using e-payments once every 3 days are light users and once every day are heavy users broadly.
- Light users face 20% times errors monthly compared to 12% of heavy users, so they don't chose e-payments more.
- Light users don't find e-payments to be readily available. So, digital payments need to be incorporated in more places.
- Light users don't find themselves to be tech-savvy enough to use e-payments. So, technicalities in e-payment apps or sites needs to be reduced to increase usage.

Limitations of the Study

- We used Judgement Sampling for our quantitative data, which has a chance of sampling errors of its own.
- Higher percentage of our In-Depth Interviews identified themselves as heavy users of e-payments. So we had lower perspective of a light user.



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Thank You For Your Time