CHAPTER 5
Usage of FinTech Services

5.1: Introduction

Accessibility and affordability of financial services are of increasing importance, which can be achieved by leveraging technology. The augmentation in penetration of mobile phones even before the pandemic and the upswing in FinTech adoption during the pandemic accentuated the potential of technology-based solutions in accelerating access, fulfilling the demand for financial services and trimming down the cost for service providers. This chapter includes the demand side analysis of the usage of FinTech services i.e., to examine the factors that impact the adoption or denial of using FinTech services. The chapter delineates the awareness and usage of FinTech services in the area of payments including Unified Payments Interface (UPI) based apps, mobile banking, internet banking, ATMs, lending-based and insurtech-based apps, FinTech applications used by most of the respondents, frequency and purpose of usage of digital financial services and motives behind using FinTech services by the bank customers. Furthermore, the factors that affect the adoption or denial of using FinTech services among the respondents were studied. For this purpose constructs from the Technology Acceptance Model [1]put forward by Davis (1989) and its extended version i.e., TAM 2 has been used. Additional constructs from the literature considered pertinent for technology adoption in urban and rural context has been used in the study.

The chapter further assesses the constraints faced in the usage of FinTech services by the respondents to gauge the relevant issues that inhibit the trouble-free use of FinTech-based technological innovations. Since the survey, was conducted amidst the first and second wave of the Covid-19 pandemic, thus, the percentage of respondents who embraced digital financial services during the pandemic and whether the pandemic resulted in an increased incidence in the use of FinTech services among the respondents has also been analysed. Thus, the chapter would provide crucial particulars associated with urban-rural technology adoption, connectivity issues, cyber-security related issues and factors significantly affecting FinTech usage, which would aid in comprehending the factors that would promote last-mile adoption of FinTech services.

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[1] For details refer to section 5.3.3 of the chapter.

5.2: AWARENESS AND USAGE OF FINTECH

5.2.1: Awareness regarding FinTech services among the respondents

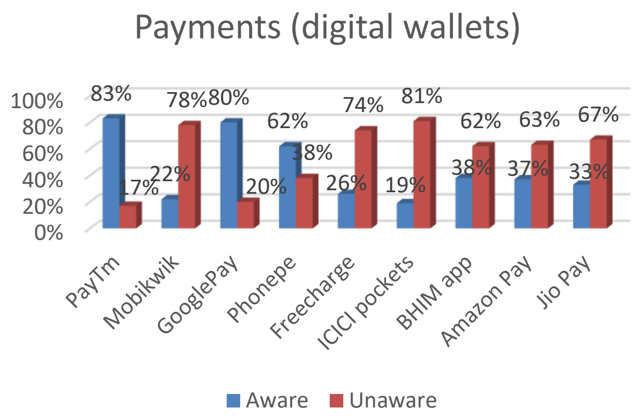

Figure 5.1: Awareness on payments (digital wallets)

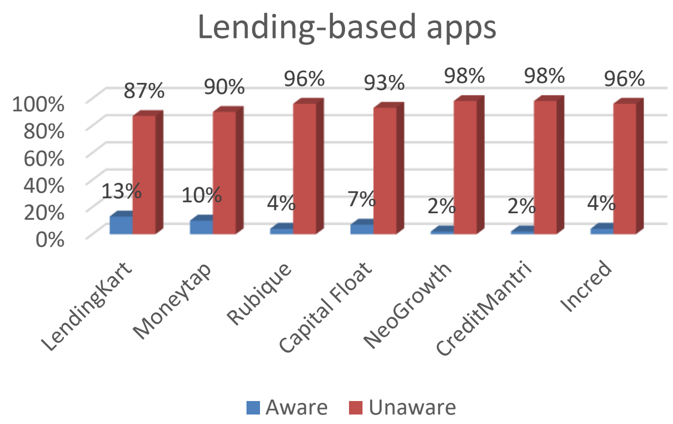

Figure 5.2: Awareness on lending-based apps

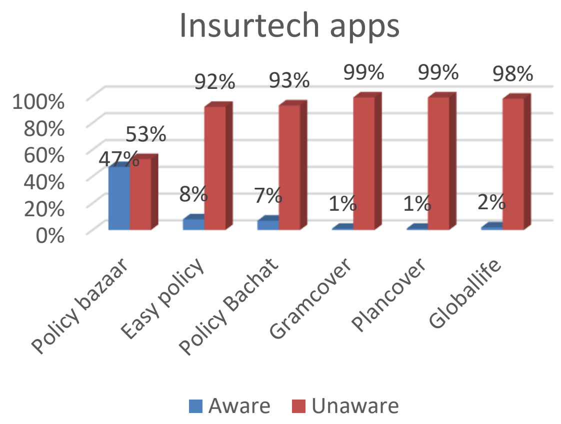

Figure 5.3: Awareness on insurtech-based apps

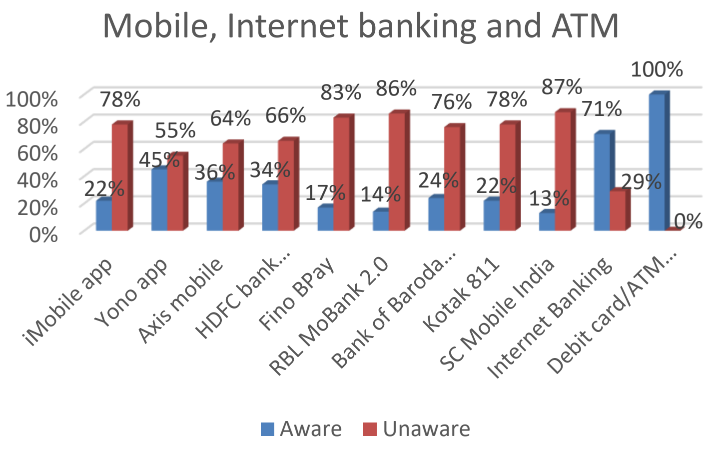

Figure 5.4: Awareness on mobile banking, internet banking and debit/ATM cards

While determining the awareness of the respondents regarding different types of FinTech services (Figure 5.1), it has been found that with regard to the payments (digital wallets), most of the respondents are aware about PayTm (83 percent), Google Pay (80 percent) followed by BHIM (38 percent), Amazon Pay (37 percent) and Jio Pay (33 percent). Besides, only 22 percent of respondents are aware of Mobikwik, 26 percent are familiar with Freecharge and 19 percent about ICICI pockets. The respondents' awareness of lending-based FinTech services (Figure 5.2) is very low. Only 13 percent of respondents are aware of lending platforms such as Lendingkart, 10 percent are conversant with Moneytap and only a handful of the respondents are cognizant with Rubique (4 percent), Capital Float (7 percent), NeoGrowth (2 percent), CreditMantri (2 percent) and Incred (4 percent).

While determining the awareness about insurtech-based financial services (Figure 5.3), it has been found that a little less than half of the respondents i.e., 47 percent are aware of insurance platforms such as Policy Bazaar and only a few respondents are aware of Easy Policy (8 percent), Policy Bachat (7 percent), Gramcover (1 percent), Plancover (1 percent) and Globallife (2 percent).

With regard to the mobile banking space (Figure 5.4), it is observed, that the majority of the respondents are aware of the Yono app of State Bank of India (45 percent), Axis mobile (36 percent) and HDFC bank mobile banking app (34 percent). The awareness of the iMobile application of ICICI Bank (22 percent), Bank of Baroda M-Connect Plus now named as BoB World (24 percent) and Kotak 811 (22 percent) is comparatively low. It has also been observed that only 17 percent, 14 percent and 13 percent of respondents are aware of Fino BPay, RBL MoBank 2.0 and SC Mobile India of Standard Chartered Bank. However, the cognizance with respect to internet banking and debit/credit cards (Figure 5.4) is found to be satisfactory. A little less than 3/4th of the respondents i.e., 71 percent are aware of internet banking whereas all the respondents i.e., 100 percent are aware of debit/ATM cards.

Thus, most of the respondents are aware of PayTm, Googlepay, Phonepe, Policybazaar, internet banking and debit cards. However, familiarity with other types of FinTech services particularly lending-based FinTech services among the respondents is extremely low.

5.2.2: Usage of FinTech services among the respondents

Table 5.1: Respondents using FinTech services

Using FinTech Services	Number	Percentage (%)
Yes	739	69.3
No	327	30.7
Total	1066	100.0

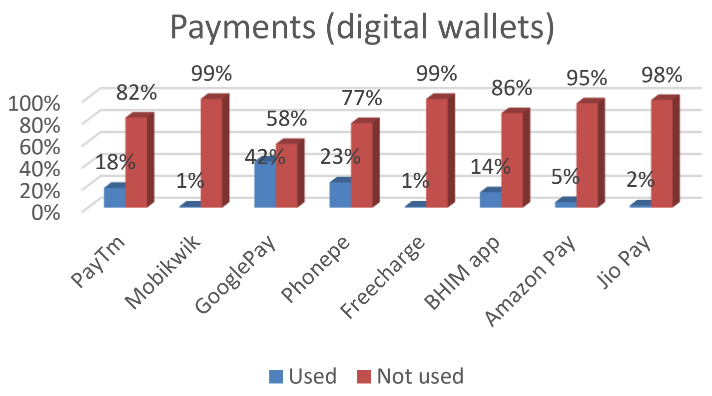

Figure 5.5: Usage of payments (digital wallets)

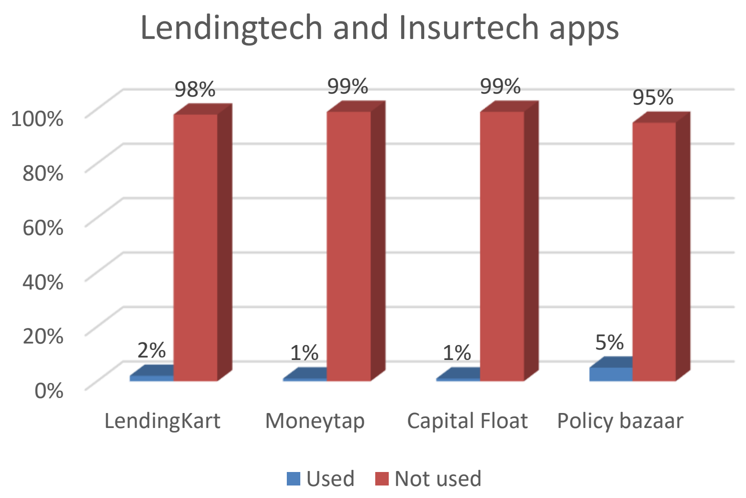

Figure 5.6: Usage of lendingtech and insurtech-based apps

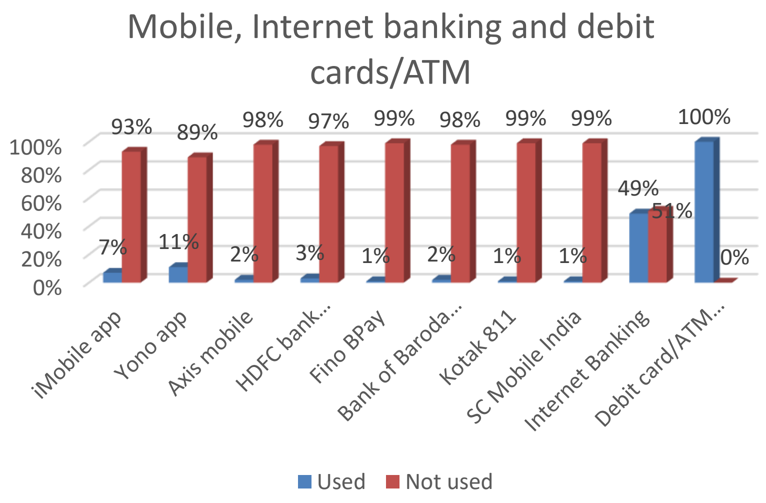

Figure 5.7: Usage of mobile, internet banking and debit/ATM cards

A little less than 3/4th of the respondents i.e., 69.3 percent are using FinTech services (Table 5.1). Among the respondents who use FinTech services, most of the respondents i.e., 42 percent use Googlepay, 23 percent use Phonepe, 18 percent use PayTm and 14 percent use the BHIM app (Figure 5.5). However, the use of Mobikwik (1 percent), Freecharge (1 percent), Amazon Pay (5 percent) and Jio Pay (2 percent) has been found only among a few respondents. While determining the use of mobile banking apps (Figure 5.7), most of the respondents use Yono app of State Bank of India (11 percent) followed by the ICICI Bank's iMobile app (7 percent). Only a few respondents use other types of mobile banking applications namely Axis mobile (2 percent), HDFC bank mobile banking app (3 percent), Bank of Baroda M-Connect plus (2 percent) and Fino BPay (1 percent). Nonetheless, the use of debit cards and internet banking is found satisfactory among the respondents as 49 percent of respondents use internet banking and cent percent use debit cards (Figure 5.7). The use of lendingtech and insurtech-based FinTech services are unpopular among the respondents as only 5 percent of respondents have used Policy Bazaar, 2 percent have used LendingKart and only 1 percent respondents have used Moneytap and Capital Float (Figure 5.6). Thus, when juxtaposed with payments-based FinTech services, the use of insurtech and lending-based FinTech services is remarkably small.

5.2.3: Use of FinTech services before the Covid-19 pandemic

Table 5.2: Frequency of respondents using FinTech services before and during the pandemic

Whether used FinTech services before the pandemic	**Frequency**	**Percentage**
Yes	698	65.5
No, I have started using such services during the pandemic	41	3.8
I still do not use such services	327	30.7
Total	1066	100.0

Source: Field Survey

The majority of the respondents i.e., 65.5 percent were using FinTech services before the Covid-19 pandemic. However, even though the number is small but it is important to note that 3.8 percent of respondents resorted to using FinTech services amidst the pandemic (Table 5.2).

5.2.4: Whether the frequency in usage of FinTech services improved during the pandemic

Table 5.3: Improvement in FinTech usage during the pandemic

Improvement in FinTech usage during the pandemic	Frequency	Percentage
Yes	478	64.7
No, it is same as before	261	35.3
Total	739	100.0

Among the respondents who are using FinTech services, it is observed that the majority of the respondents' FinTech usage improved during the pandemic (Table 5.3). Thus, it can be ascribed that the Covid-19 pandemic has resulted in the uprise of FinTech usage among the respondents.

5.2.5: Frequency in the usage of FinTech services

Table 5.4: Frequency of usage of FinTech services

Frequency of usage	Number	Percentage (%)
At least once in a week	172	23.3
Bi-weekly once	117	15.8
At least once in a month	274	37.1
Other than above	176	23.8
Total	739	100.0

Source: Field Survey

A considerable portion of the respondents (37.1 percent) use FinTech services at least once in a month (Table 5.4). In the study, the respondents who are using any type of FinTech service 'at least once in a week', 'bi-weekly once', or 'at least once in a month' are considered high-end users and the frequency of usage 'other than the above' are considered as low-end users. Thus, considering the cumulative figures, it has been found that 76.2 percent of respondents are high-end users and 23.8 percent of respondents are low-end users.

5.2.6: Socio-demographic characteristics and usage of FinTech services

This section aims to find out the relationship between respondents' socio-demographic characteristics such as gender, age, occupation, educational qualification, annual income, area of residence, religion, social group and usage of FinTech services (as shown in Table 5.1). The hypotheses formulated along with the test results are as follows

5.2.6a: Gender and usage of FinTech services

H_0: There is no association between gender and usage of FinTech services

H_1: There is association between gender and usage of FinTech services

Table 5.5: Chi-square between gender and usage of FinTech services

Gender	Usage of FinTech services (%)		Chi-square	df	p value
	Yes	No			
Male	72.8	27.2	24.537	1	0.000
Female	55.1	44.9			

As compared to 72.8 percent males, only 55.1 percent females use FinTech services (Table 5.5). The Chi-square test result revealed that there is a strong association (measures of strength of association as used by Akoglu, 2018; Adhikary & Das, 2021) between usage of FinTech services and gender (Chi-square = 24.537, p = 0.000, Phi = 0.152). Thus, there is sufficient evidence to reject the null hypothesis at 0.05 level of significance.

5.2.6b: Age and usage of FinTech services

H_0: There is no association between age and usage of FinTech services

H_1: There is association between age and usage of FinTech services

Table 5.6: Chi-square between age and usage of FinTech services

Age	Usage of FinTech services (%)		Chi-square	df	p value
	Yes	No			
18-28 years	95.3	4.7	208.137	3	0.000
29-39 years	90.0	10.0			
40-50 years	70.3	29.7			
Above 50 years	42.3	57.7			

While determining the association between age and usage of FinTech services, it is observed that 95.3 percent, 90 percent and 70.3 percent of respondents in the age bracket 18-28 years, 29-39 years and 40-50 years are users of FinTech services. However, more than half of the respondents belonging to the age category above 50 years are non-users of FinTech services. The result of the Chi-square test (Chi-square = 208.137, p = 0.000, Cramer's V = 0.442) also revealed that there is a very strong association between age and usage of FinTech services thereby generating sufficient evidence to reject the null hypothesis at 0.05 level of significance.

5.2.6c: Occupation and usage of FinTech services

H_0: There is no association between occupation and usage of FinTech services

H_1: There is association between occupation and usage of FinTech services

Table 5.7: Chi-square between occupation and usage of FinTech services

Occupation	Usage of FinTech services (%)		Chi-square	df	p value
	Yes	No			
Businessman/trader	97.7	2.3	483.122	5	0.000
Agriculturist	34.8	65.2			
Govt. service/PSUs	100	0			
Private service	86.6	13.4			
Self-employed/Professionals	100	0			
Daily wage earner	25.3	74.7			

Majority of the businessmen/traders (97.7 percent), Government employees (100 percent), respondents with private service (86.6 percent) and self-employed/professionals (100 percent) are the users of FinTech services. Besides, only 34.8 percent of agriculturists and 25.3 percent daily wage earners use FinTech services (Table 5.7). The value of Chi-square = 483.122, p = 0.000, and Cramer's V = 0.673 also shows that there is a very strong association between occupation and usage of FinTech services.

5.2.6d: Annual income and usage of FinTech services

H_0: There is no association between annual income and usage of FinTech services

H_1: There is association between annual income and usage of FinTech services

Table 5.8: Chi-square between annual income and usage of FinTech services

Annual Income	Usage of FinTech services (%)		Chi-square	df	p value
	Yes	No			
Till Rs. 2,50,000	47	53	336.371	4	0.000
Rs. 2,50,001-Rs. 5,00,000	99	1			
Rs. 5,00,001-Rs. 7,50,000	100	0			
Rs.7,50,001-Rs. 10,00,000	100	0			
Above 10,00,000	100	0			

It is observed that cent percent of respondents with an income level above Rs. 5,00,000 use FinTech services in contrast to 47 percent of respondents with an annual average income up to Rs. 2,50,000 (Table 5.8). The test results (Chi-square = 336.371, p = 0.000, Cramer's V = 0.562) revealed that there is a very strong association between annual average income and usage of FinTech services thereby rejecting the null hypothesis at significance level of 0.05.

5.2.6e: Educational qualification and usage of FinTech services

H_0: There is no association between educational qualification and usage of FinTech services

H_1: There is association between educational qualification and usage of FinTech services

Table 5.9: Chi-square between educational qualification and usage of FinTech services

Educational Qualification	Usage of FinTech services		Chi-square	df	p value
	Yes (%)	No (%)			
Illiterate	0	100	703.207	7	0.000
Primary	9.9	90.1			
Below HSLC	53.5	46.5			
HSLC	90.0	10.0			
HSSLC	93.0	7.0			
Graduate	99.1	0.9			
Post-graduate and above	100	0			
Did not attend school	11.4	88.6			

It is found that cent percent of the respondents with educational qualification of post-graduate and above, 99.1 percent of graduates, 93 percent who passed 12^{th} (HSSLC) and 90 percent with matriculation (HSLC) are the users of FinTech services as compared to 9.9 percent of respondents with primary level education and none of the illiterate respondents have used FinTech services (Table 5.9). The test results revealed that there is a very strong association between educational qualification and the use of FinTech services (Chi-square = 703.207, p = 0.000, Cramer's V = .812) which resulted in the rejection of the null hypothesis at 0.05 level of significance.

5.2.6f: Area of residence and usage of FinTech services

H_0: There is no association between area of residence and usage of FinTech services

H_1: There is association between area of residence and usage of FinTech services

Table 5.10: Chi-square between area of residence and usage of FinTech services

Area of residence	Usage of FinTech services (%)		Chi-square	df	p value
	Yes	No			
Urban	97.3	2.7	62.082	1	0.000
Rural	64.9	35.1			

While examining the association between the area of residence and FinTech usage, it is found that 97.3 percent of respondents in urban areas use FinTech services in comparison to 64.9 percent of respondents in rural areas (Table 5.10). It is also discernible from the test results (Chi-square = 62.082, p = 0.000, Phi = .241) that there is a strong association between the area of residence and use of FinTech services.

5.2.6g: Religion and usage of FinTech services

H_0: There is no association between religion and usage of FinTech services

H_1: There is association between religion and usage of FinTech services

Table 5.11: Chi-square between religion and usage of FinTech services

Religion of the respondents	Usage of FinTech services (%)		Chi-square	df	p value
	Yes	No			
Hinduism	70.4	29.6	13.918	3	0.003
Islam	68.7	31.3			
Christianity	49	51			
Jainism	100	0			

It is found that cent percent of respondents belonging to Jainism use FinTech services, followed by 70.4 percent of Hindus, 68.7 percent of respondents belonging to Islam and 49 percent of Christians. The test results (Chi-square = 13.918, p = 0.003, Cramer's V = 0.114) revealed that religion and the use of FinTech services share a significant and moderate association. Thus, the null hypothesis is rejected at level of significance 0.05.

5.2.6h: Social group and usage of FinTech services

H_0: There is no association between social group and usage of FinTech services

H_1: There is association between social group and usage of FinTech services

Table 5.12: Chi-square between social group and usage of FinTech services

Social group of the respondents	Usage of FinTech services (%)		Chi-square	Df	p value
	Yes	No			
Scheduled tribe	63.2	36.8	26.637	3	0.000
Scheduled caste	65.9	34.1			
Other backward classes	63.3	36.7			
Others	78.8	21.2			

It is observed that the majority of the respondents i.e., 78.8 percent of respondents belonging to others/general (forward category) use FinTech services. Furthermore, the use of FinTech services among the respondents from scheduled tribes, scheduled castes and other backward classes are 65.9 percent, 63.2 percent and 63.3 percent respectively (Table 5.12). It is also evident from the Chi-square test that social group and usage of FinTech services share a strong association (Chi-square = 26.637, p = 0.000, Cramer's V = 0.158) thereby rejecting the null hypothesis at 0.05 level of significance. The analysis revealed that usage of FinTech services is prominent among the forward classes as compared to the respondents belonging to scheduled tribes, scheduled castes and other backward classes, which makes it imperative to promote digital financial education, especially among the backward classes.

5.3: Benefits, Adoption and Difficulties

This section discusses the purposes for which FinTech services are used and identifies the reasons behind respondents' shift toward digital payment methods. In addition, the factors that influence the adoption/non-adoption of FinTech services are analysed using components from the TAM model and other constructs from the literature. The remainder of the section is devoted to identifying the challenges experienced by various demographic profiles when using FinTech services.

5.3.1: Purpose for using FinTech services by the respondents

Table 5.13 Purposes of usage of FinTech services by the respondents

Purposes	**Yes (%)**	**No (%)**
Transfer money	63.2	36.8
Recharge mobile	56.8	43.2
Shopping in stores	46.1	53.9
Purchase from e-commerce companies	42.5	57.5
To avail special offers on some retail products	20.0	80.0
Purchase of flight/railway/bus tickets	35.2	64.8
To pay utility bills	35.0	65.0
To pay school/college fees	15.2	84.8
Withdraw cash	35.2	64.8

Source: Field Survey, **Note:** This section has multiple responses

While determining the purposes for using FinTech services by the respondents, it is observed that 63.2 percent of respondents use FinTech services to transfer money (Table 5.13). More than half (56.8 percent) of the respondents recharge from their telecom service providers using FinTech-based applications. The respondents also use technology-based financial services while shopping from stores (46.1 percent) and purchasing from e-commerce companies (42.5 percent). This can be attributed to Unified Payment Interface (UPI) based apps getting much traction, especially amidst the Covid-19 pandemic and ease of using Quick Response (QR) code while making transactions thereby resulting in the surge of usage of FinTech services. Moreover, the use of digital financial services to purchase flight/railway/bus tickets (35.2 percent) and to pay utility bills (35 percent) is found only among a few respondents. Some of the respondents (35.2 percent) use their debit cards to withdraw cash and not to make purchases online or through Point of Sale (PoS). Thus, for supplanting cash-based payments and to acquire the benefit of seamless FinTech-based payments, the respondents should be stimulated to use debit cards not only to withdraw cash but also to make digital transactions. Besides, the use of digital financial services in paying school/college fees (15.2 percent) is found to be very low among the respondents. Even though online payment facilities have been given by many schools/colleges for fee payment amidst the pandemic but the preference for cash during fee payment is found to be dominant over digital payment. It is relevant to note that 20 percent of respondents use technology-based financial services to avail of special offers on different products.

5.3.2: Reasons for the respondents' shift towards digital mode of payments

Nine statements have been used to determine the reasons that motivated the respondents for the shift towards digital modes of payment using the five-point scale of agreement (interval scale) where 1 indicates 'least agreed' and 5 indicates 'most agreed'. The percentage under each statement is given below in Table 5.14

Table 5.14: Reasons for shift towards digital modes of payment

Reasons	**1**	**2**	**3**	**4**	**5**
No need to carry huge cash	0	0	2.4	19.8	77.8
Provides cashback offers	29.2	36.7	13.8	6.2	14.1
Easy and fast way to make payments	0	0	0.8	28.0	71.2
Easy and fast way to track the record of payments	0	0	0.4	24.4	75.2
Provides 24*7 transfer	0	0	1.1	27.1	71.8
Discounts and reward points	30.8	34.6	11.9	7.6	15.1
It is time-saving	0	0	1.0	26.0	73.0
Helps in expense management	0	2.0	6.2	21.7	70.1
It has become trendy/order of the way	0	1.0	1.2	11.4	86.4

Source: Field Survey

The majority of the respondents mostly agreed that the reasons for the shift towards the digital mode of payment are FinTech-based payments have become trendy/order of the way (86.4 percent), non-requirement to carry huge cash (77.8 percent), 24x7 transfer (71.8 percent), easy and fast way to make (71.2 percent) and track the record of payments (75.2 percent) (Table 5.14).

Furthermore, Exploratory Factor Analysis (EFA) is used to determine whether the several items mentioned in Table 5.14 fall into different clusters. Factor analysis is a procedure of data reduction and summarization. Factor analysis determines whether several items in the questionnaire assemble into a few clusters where each cluster is considered as a separate construct (Streiner, 1994). Thus, to analyse the underlying relationship between the measured variables EFA has been used. The first step in factor analysis is to check the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and ideally, the number of variables x 10 is desirable (Gorsuch, 1983 as cited by Worthington & Whittaker, 2006).

Secondly, Bartlett’s Test of Sphericity is used to check that the correlation matrix is factorable (Eaton, Frank, Johnson & Willoughby, 2019). To run a factor analysis Bartlett’s Test of Sphericity should be significant (Table 5.15).

Table 5.15: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.774
Bartlett's Test of Sphericity	Approx. Chi-Square	3153.317
	df	36
	Sig.	.000

In EFA, Extraction and Rotation are two important steps. In the study, Principal Component Extraction Method with Orthogonal rotation i.e., Varimax rotation has been used for data reduction and the number of factors that have Eigen values exceeding 1 are retained. Eigen value represents the total variance that each factor explains, as factors with Eigen values less than 1 are considered unstable (Kaiser, 1958). All factor loadings are suppressed to less than 0.3 (Field, 2013). The results of EFA are discussed below:

Communality refers to the sum of squared factor loadings (Zeller, 2005), in simple terms, it refers to the amount of variance a variable shares with all other variables being considered. According to Child (2006), an item with a communality score of less than 0.2 must be removed from the analysis. Other studies also suggest that the communality score between 0.25 to 4 are acceptable with the ideal score being 0.7 or above (Beavers et. al, 2013 as cited by Eaton, Frank, Johnson & Willoughby, 2019).

Table 5.16: Communalities score for each item

Communalities

	Initial	Extraction
No need to carry huge cash	1.000	.413
Provides cashback offers	1.000	.941
Easy and fast way to make payments	1.000	.674
Easy way to track the records of payments	1.000	.599
Provides 24*7 transfer	1.000	.531
Discounts and reward points	1.000	.934
It is time-saving	1.000	.492
Helps in expense management	1.000	.494
It has become trendy/order of the way	1.000	.490

Extraction Method: Principal Component Analysis

Table 5.16 revealed that the communality score of the items ranges from .413 to .941. As none of the item communality is less than the cut-off value, thus, none of the items were removed from the analysis. The number of factors retained is observed from Eigen values more than 1 and an inspection of the scree plot. The total variance explained table (Table 5.17) shows the percentage of variance attributed to each factor. Two factors with Eigen values exceeding 1 have been retained and the factors together explain 61 percent of the variance, which is above the cut-off range. The general rule is that the retained factors must explain at least 50 percent of the total variance (Streiner, 1994).

Table 5.17: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.661	40.683	40.683	3.661	40.683	40.683	3.570	39.666	39.666
2	1.907	21.185	61.868	1.907	21.185	61.868	1.998	22.203	61.868
3	.803	8.917	70.785						
4	.696	7.730	78.515						
5	.583	6.482	84.997						
6	.479	5.319	90.316						
7	.465	5.161	95.477						
8	.324	3.597	99.074						
9	.083	.926	100.000						

Extraction Method: Principal Component Analysis.

Table 5.18: Rotated Component Matrix[a]

	Component	
	1	2
Easy and fast way to make payments	.797	
Easy way to track the records of payments	.770	
Provides 24*7 transfer	.713	
Helps in expense management	.702	
It is time-saving	.701	
It has become trendy/order of the way	.662	
No need to carry huge cash	.632	
Provides cashback offers		.966
Discounts and reward points		.965

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

The rotated component matrix table 5.18 revealed that the number of items that load on both factors. It has been observed that the items 'Easy and fast way to make payments', 'Easy way to track record of payments', 'Provides 24x7 transfer', 'Helps in expense Management', 'It is time-saving', 'It has become trendy/ order of the way', 'No need to carry huge cash' has loaded on Factor 1 (7 items) and the items 'Provides cashback offers' and 'Discounts and reward points' has loaded in Factor 2 (2 items). A factor with 2 items is considered reliable if the variables under the factor are highly correlated with r>.7 and are fairly uncorrelated with other items (Yong & Pearce, 2013; Yoo & Donthu, 2000; Worthington & Whittaker, 2006). It has been observed from the correlation matrix (Annexure J) that variables in Factor 2 are highly correlated (r>.7) and uncorrelated with other variables thereby retaining Factor 2. The Cronbach's Alpha co-efficient of both the factors is greater than the acceptable limit of 0.7 showing good internal consistency.

As the aim of performing EFA is to provide meaningful names to the group of items that are loaded on each factor (Birmingham City University, 2017). Factor 1 have been named 'Convenience' and Factor 2 as 'Offers' (see Figure 5.8)

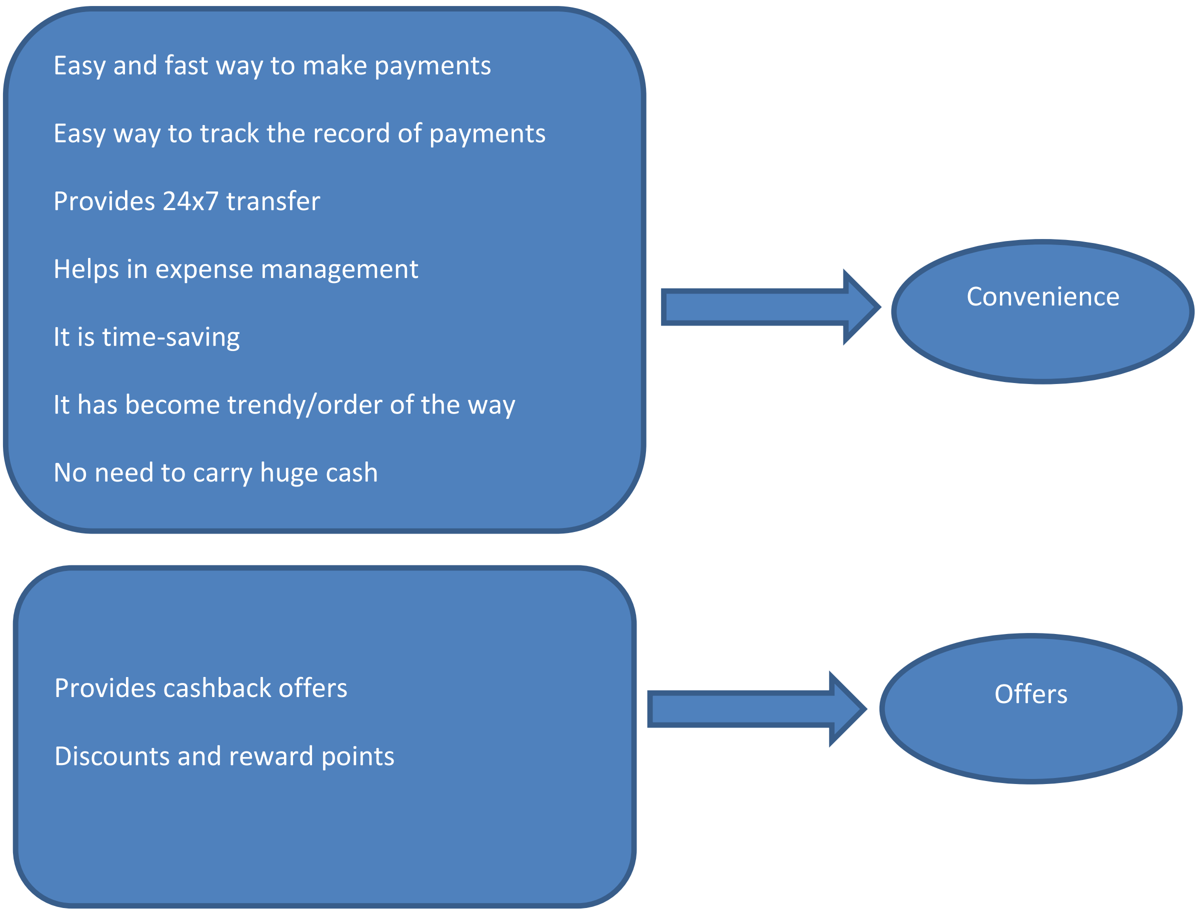

Figure 5.8: Items loaded on both the factors.

Thus, it is found that Convenience and Offers provided by FinTech services are the two important factors that have motivated bank customers to shift towards digital modes of payment.

5.3.3: Factors affecting adoption/non-adoption of FinTech services

The Technology Acceptance Model (TAM) developed by Davis (1989) assists in determining the desirability of people's use of technology and relies on two key factors i.e., Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). The perceived usefulness of a system or technology is the extent to which a person believes that its use will result in enhanced performance. Perceived Ease of Use is the degree to which an individual contemplates that the use of a particular system is easy and effortless or trouble-free (Davis, 1989; Davis, Bagozzi & Warshow, 1989). TAM posits that PU and PEOU jointly determine the attitude towards a particular technology i.e., an individual’s feeling about performing a behaviour. Attitude further influences one’s intent to perform a particular behaviour (Behavioural Intention) which in turn affects actual usage. Over and above both TAM and the Theory of Reasoned Action (TRA by Fishbein & Ajzen, 1975) put forward, that Behavioural Intention is a vital determinant of actual usage of a particular technology and that other factors affect usage indirectly through Behavioural Intention. TAM also postulated that Perceived Ease of Use influences Perceived Usefulness i.e., a particular technology, which is easy to use would result in augmentation of usefulness among the users. TAM was further developed and congruous to the Theory of Reasoned Action by Fishbein & Ajzen (1975), Taylor & Todd (1995), the impact of Social Influence on the usage of technology was scrutinised. Social Influence means a person’s belief of using or not using a system and is motivated by a referent whom the individual considers important (such as relatives, peers and society). Moreover, a significant result was obtained on the influence of network externalities (social Influence) on Behavioural Intention. During the course of time, many researches conducted on technology adoption found a positive impact of social influence on technology acceptance behaviour.

Moreover, additional constructs from the literature considered appropriate in studying technology acceptance along with TAM has been used to determine the factors that influence the adoption or denial in using FinTech services. These are explained below:

Trust: Trust is an crucial factor leading to FinTech service adoption (Le, 2021). According to Urban, Amyx & Lorenzon (2009), lack of trust refrains bank customers from using

FinTech services. Data privacy and security of transactions i.e., a safe and secure transaction system are important motivators in ensuring trust towards FinTech services. If customers are satisfied with the confidentiality of data, safety of transactions provided by a system then it would result in an increase in the level of trust in using FinTech services. Studies focusing on technology-based financial systems have found a significant influence of trust on the attitude and intention to use the service (Chandra, Srivastava & Theng, 2010; Hu et al, 2019; Shin, 2009). Considering the dominant role of trust in driving an individual's adoption of a particular service, therefore, the respondents' perception of trust in influencing the attitude towards FinTech service is studied. Furthermore, Le (2021) found that trust is the most important consideration in influencing FinTech usage intention during the lockdown on Covid-19 and viewed that increased security, usefulness and efficient services would aid in the continued use of FinTech services even aftermath of the pandemic.

Government support: Government support aids in improving the dependability and authenticity of the products and services thereby escalating the acceptance among potential users (Hu et al, 2019). Significant progress has been made by the Indian government in the use of FinTech-based innovations through the Digital India initiative, the launch of UPI, the Aadhaar Enabled Payment System (AePS), the creation of a regulatory sandbox for live testing of FinTech innovations, the formation of payment banks to further last mile access to digital financial services. In addition, the creation of the Payment Infrastructure Development Fund (PIDF) to provide a fillip to payment infrastructure in tier 3 to tier 6 centres and North East states. Covid-19 has hastened digital innovations, which was already underway and the Government policies adopted to deliver financial assistance through technology-based innovations (Financial Stability Board, 2022) such as the transfer of direct benefit to Aadhaar-linked Jan Dhan bank account holders have resulted in a positive effect on technology-based financial services thereby reducing the digital divide. Empirical studies have found a significant influence of Government support in the use of FinTech services (Hu et. al, 2019; Marakarkandy, 2013). Government support is found to have a direct effect on trust towards FinTech services (Marakarkandy, 2013). Taking into consideration the Government's role such as investing in infrastructure, policy formulation, consumer protection and reducing the digital divide in promoting FinTech-based innovations, the influence of Government support on the respondents' attitude regarding FinTech services is determined for the purpose of the study.

Self-efficacy: Self-efficacy signifies an individual's capacity to carry out a specified task (Bandura 1986 as cited by Chao, 2019). According to Igbaria & Livari (1995), an individual's perception of a system/service being complex results in a less likely intention in using the system/service. Studies conducted using self-efficacy to determine the adoption of FinTech services are identified to have a significant influence on using FinTech services (Hasan, 2007; Mallya, Lakshminarayanan & Payini, 2019; Wu, Wang & Lin, 2007) establishing the theoretical underpinning that higher self-efficacy results in a positive intention to use FinTech services. Furthermore, according to Bandura (1982) as cited by Davis, Bagozzi & Warshaw (1989), if a system is easy to interact with then it results in an increased sense of self-efficacy among the users. Consistent with this, empirical researches have identified self-efficacy as a vital determinant of ease of use and found that self-efficacy in using technology has a positive influence on Perceived Ease of Use (Al-Haderi, 2013; Venkatesh & Davis, 1996).

Perceived risk: Perceived risk means the feeling of vulnerability and the plausible negative outcomes of using a service (Keong, Leong & Bao, 2020; Meyliana, Fernando & Surjandy, 2019). The risk in terms of financial loss during a transaction (financial risk), susceptibility to cyber-attack (security risk), use of personal/financial information without consent from the user of the service (privacy risk), inaccuracy of the payment method (functional risk) can have a negative influence on an individual's mind regarding the use of technology-based financial services (Keong, Leong & Bao, 2020; Noreen, Ghazali & Mia, 2021). Studies reveal that perceived risk is a crucial factor, which negatively influences the attitude and intention towards FinTech services (Kesharwani & Bisht, 2012; Nguyen & Nguyen, 2017; Singh & Rajeev, 2021). High perceived risk dampens the effect of Perceived Usefulness on intent to use (Im, Kim & Han, 2008). Furthermore, studies have found that perceived risk in using technology-based financial services has a negative influence on trust towards such services (Hu et. al, 2019; Kim & Prabhakar, 2000 as cited by Hu et al., 2019).

Thus, based on the aforementioned theoretical foundations and the constructs found in section 5.3.2, the following hypotheses have been formed

H_1: Perceived Usefulness has a significant effect on the attitude towards FinTech services

H_2: Perceived Ease of Use has a significant effect on the attitude towards the use of FinTech services

H_3: Perceived Ease of Use significantly affects Perceived Usefulness of FinTech services

H_4: Trust towards FinTech services has a significant positive effect on attitude to use FinTech services

H_5: Government support has a positive direct effect on trust towards FinTech services

H_6: Government support has a direct effect on attitude towards FinTech services

H_7: Perceive risk negatively impacts the trust towards FinTech services

H_8: Perceived risk negatively impacts the attitude towards FinTech services

H_9: Convenience has a direct effect on the trust towards FinTech services

H_{10}: Offers by the FinTech service providers have a significant effect on trust towards FinTech services

H_{11}: Self-efficacy has a significant effect on attitude towards FinTech services

H_{12}: Self-efficacy has a significant direct effect on Perceived Ease of Use towards FinTech services

H_{13}: Social influence has a significant impact on attitude to use FinTech services

H_{14}: Perceived Usefulness significantly affects Behavioural Intention to use FinTech services

H_{15}: Perceived Ease of Use has a significant effect on the Behavioural Intention to use FinTech services

H_{16}: Social Influence has a significant effect on the Behavioural Intention to use FinTech services

H_{17}: Self-efficacy significantly affects the Behavioural Intention to use FinTech services

H_{18}: Attitude towards FinTech services has a significant impact on the Behavioural Intention to use FinTech services

H_{19}: Behavioural Intention to use FinTech services significantly impact actual usage of FinTech services

5.3.3a Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is done to test how well the variables that are being measured constitute the constructs. CFA assists in the judgement of fit between the observed data and the theoretical model, which assesses the causal relationship between the latent constructs and the observed variables. The results of CFA provide different model fit indices, however, reporting all the model fit indices is not necessary (Hooper, Coughlan & Mullen, 2008 as cited by Gurung, 2020). According to Kline (2005), as cited by Wiley (2020), the model fit indices such as Chi-square, Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR) and Root Mean Square Error of Approximation (RMSEA), should be reported. Some studies opt to report one from each of the three indices i.e., absolute, incremental and parsimonious (Awang, 2015). Thus, based on the above-stated literature the most widely used model fit indices are provided in Table 5.20. The Factor loadings from CFA are also given in Table 5.19. Factor loadings should be greater than 0.5 and ideally 0.7 (Hair, Babin, Babin & Anderson, 2010). From Table 5.19, it is observed that the factor loadings of all the measured variables are greater than the threshold limit of 0.7.

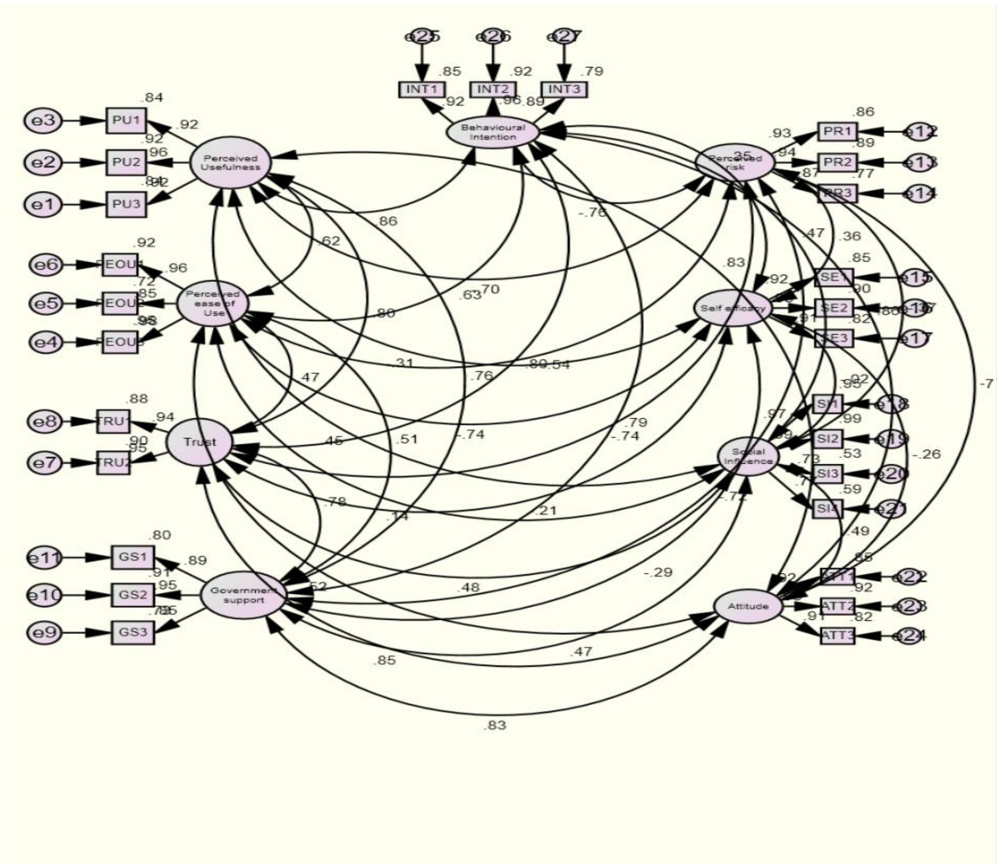

Figure 5.9: CFA measurement model

Table 5.19: Factor Loadings from CFA

Constructs	Items	Factor Loadings								
Perceived Usefulness	PU1	.916								
	PU2	.957								
	PU3	.916								
Perceived Ease of Use	PEOU1		.958							
	PEOU2		.848							
	PEOU3		.977							
Trust	TRU1			.939						
	TRU2			.948						
Government Support	GS1				.893					
	GS2				.952					
	GS3				.852					
Perceived Risk	PR1					.927				
	PR2					.943				
	PR2					.875				
Self-efficacy	SE1						.923			
	SE2						.951			
	SE3						.907			
Social Influence	SI1							.974		
	SI2							.994		
	SI3							.727		
	SI4							.771		
Attitude	ATT1								.921	
	ATT2								.960	
	ATT3								.905	
Behavioural Intention	INT1									.922
	INT2									.959
	INT3									.890

5.3.3b Assessment of model fit:

The model fit indices reported in the study are

Chi-square/degree of freedom ($\chi 2$/df): $\chi 2$/df indicates the extent to which the proposed theory matches the data (Hooper, Coughlan & Mullen, 2008). The threshold limit for a good model fit is within 0.2 to 0.5 (Tabachnick & Fidell, 2007; Wheaton, Muthen, Alwin & Summers, 1977 as cited by Hooper, Coughlan & Mullen, 2008).

Root Mean Square Error of Approximation (RMSEA): RMSEA assesses that for not known but optimally chosen parameter estimates would fit the population covariance matrix. A value less than 0.8 indicates a good fit (Browne & Cudeck, 1993; MacCallum, Browne & Sugawara, 1996).

Normed Fit Index (NFI): The $\chi 2$ of the model developed and the null model is compared by NFI. Here, the null model describes that the variables under measurement are uncorrelated. The recommended threshold for NFI is >.90 (Bentler & Bonnet, 1980; Bollen, 1989).

Comparative Fit Index (CFI): CFI is one of the popular model fit indices that are being reported because it provides accurate results even when the sample size is small and is assumed by comparing the sample covariance matrix with the null model. The acceptable value is >.90 (Hair, Babin, Babin & Anderson, 2010; Hu & Bentler, 1999).

Tucker-Lewis Index or Non-Normed Fit Index (TLI): TLI is also not sensitive to sample size and evaluates the model by substantiating the correlation between the variables (Gurung, 2020). The acceptable threshold for TLI is >.90 (Tucker & Lewis, 1973).

Standardized Root Mean Square Residual (SRMR): SRMR is the square root of the contrast between the sample residuals and the hypothesized covariance model and the recommended value is <0.05 (Byrne, 1998), however, values <0.08 also indicate a good fit (Cho, Hwang, Sarstedt & Ringle, 2020; Hooper, Coughlan & Mullen, 2008; Hu & Bentler, 1999).

The values obtained from the CFA model fit indices are shown below in Table 5.20

Model Fit Indices	$\chi 2$	df	p value	$\chi 2$/df	NFI	TLI	CFI	SRMR	RMSEA
Values obtained	1192.096	288	0.000	4.14	.957	.957	.965	.0605	.065
Acceptable threshold				2.0 – 5.0	>.90	>.90	>.90	<.08	<.08

The $\chi 2$, df and the significant value are sensitive to sample size (Hooper, Coughlan & Mullen, 2008) and the p value displays significant results when the sample size is large (Bagozzi & Yi, 1988; Marakarkandy, 2013). Thus, in the study, the reason for the significant p value would be a sample size of 1066.

The model fit values are within the recommended threshold, indicating that the model is acceptable.

5.3.3c Reliability and validity:

The reliability of the constructs used for determining technology adoption is also measured by Composite Reliability (CR), and Convergent validity is measured using Average Variance Extracted (AVE).

Composite Reliability (CR): Composite Reliability measures the internal consistency of the items measured by the construct. CR values more than 0.7 is considered to be acceptable (Byrne, 2001).

The formula for calculating Composite Reliability
$(\sum \text{Ƙ})^2 / [(\sum \text{Ƙ})^2 + (\sum 1- \text{Ƙ}^2)]$ (Ahmad, Zulkurnain & Khairushalimi, 2016; Marakarkandy, 2013)

Where, Ƙ = factor loading of each item

n = number of items

Convergent validity: Convergent validity checks whether or not the scale items are closely related and is measured by calculating the Average Variance Extracted (AVE) i.e., on average how much variations in the items can be explained by the construct. The AVE value >0.5 for a construct is considered to have adequate convergent validity (Fornell & Larcker, 1981).

The formula for AVE = $\sum \text{Ƙ}^2/n$

Table 5.21: Reliability and validity measures

Constructs	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Usefulness	.916	.865
Perceived Ease of Use	.918	.864
Trust	.942	.890
Government Support	.927	.810
Perceived Risk	.939	.838
Self-efficacy	.948	.860
Social Influence	.927	.765
Attitude	.857	.863
Behavioural Intention	.892	.854

Acceptable value of CR = > 0.7 and AVE is > 0.5

The Composite Reliability for the nine constructs is > 0.7 thus, establishing internal consistency and the AVE for the nine constructs is more than the recommended value of 0.5, thereby establishing convergent validity.

Discriminant validity: Discriminant validity is used to see that the items that conceptually should not be related to each other are, in fact, unrelated. To establish discriminant validity, the AVE values for each construct is checked with the correlation among the constructs. According to (Fornell & Larcker, 1981; Hair, Black, Babin, Anderson & Tatham, 2006) if AVE is higher than the square of inter-construct correlation or the square root of AVE is higher than the inter-construct correlation then discriminant validity is established. In this study, the criteria for discriminant validity followed is AVE of the construct must be greater than the squared inter-construct correlation (Marakarkandy, 2013).

Table 5.22: The value of AVE, correlation and squared inter-construct correlations

	PU	PEOU	TRU	GS	PR	SE	SI	ATT	BI
PU	**0.865**	0.378	0.632	0.575	0.49	0.098	0.198	0.687	0.529
PEOU	0.615	**0.864**	0.222	0.257	0.293	0.548	0.019	0.268	0.629
TRU	0.795	0.471	**0.89**	0.610	0.543	0.042	0.231	0.726	0.629
GS	0.758	0.507	0.781	**0.81**	0.523	0.082	0.221	0.424	0.579
PR	-0.7	-0.541	-0.737	-0.723	**0.838**	0.128	0.135	0.067	0.579
SE	-0.313	-0.74	-0.205	-0.287	0.358	**0.86**	0.0005	0.067	0.120
SI	0.445	0.138	0.481	0.47	-0.367	-0.022	**0.765**	0.244	0.222
ATT	0.829	0.518	0.852	0.651	-0.754	-0.258	0.494	**0.863**	0.464
BI	0.727	0.625	0.793	0.68	-0.761	-0.347	0.471	0.681	**0.854**

The values in diagonal (in black) are the Average Variance Extracted (AVE), the values below the AVE are the correlation among the constructs (in blue) and the values above the AVE are the squared inter-construct correlation (in red). It can be observed from the table that the AVE for each construct is higher than the squared inter-construct correlations, thereby establishing discriminant validity.

After verifying the item loading into the respective constructs, for examining the factors that affect the adoption or denial of using FinTech services linear regression has been used. The assumptions necessary to conduct linear regression have been checked before performing the analysis.

The assumption of linearity among the dependent and independent variables is checked using a scatter plot and the results shown by the scatter plot diagram depicted that the linearity assumptions for the variables are not violated. Normality is examined by inspecting the skewness and kurtosis and a visual examination of the histogram. According to George & Mallery (2010), acceptable skewness and kurtosis values range between +2 and -2.. In addition, Byrne (2010) and Hair et. al (2010) state that, value of skewness ranging between +2 and -2 and kurtosis ranging between +7 and -7 are considered acceptable. The value of skewness and kurtosis are found to be below the cut-off range of +2 and -2 as suggested by George & Mallery (2010). Further, QQ plots have been examined to check that the data tend to follow a diagonal line and have a linear pattern. The assumption of homoscedasticity is checked by plotting the residuals and predicted values on the scatterplot. The examination of the scatter plot of standardised residual and standardised predicted value has shown a random dispersion around zero, in simple terms, the scatter plots showed a rectangular pattern of dots. An important assumption of regression is multicollinearity, which means that the independent variables (predictor variables) should not be highly correlated with each other. According to Hair et. al (1998) and Sekaran (2006) the prescribed cut-off is less than 0.8. Multicollinearity is examined by the correlation matrix for the independent variables, Tolerance and Variance Inflation Factor (VIF). The threshold limit for VIF is <10 and for Tolerance is >.10 (Cohen, Cohen, West & Aiken, 2003). As the data fulfils the criteria as specified in the literature for correlation among the independent variables, VIF and Tolerance, thus, the data do not have the problem of multicollinearity.

After checking the assumptions of linear regression, analysis has been done to determine the factors that affect the adoption or denial in using FinTech services and the results are discussed below

5.3.3d Results of Regression Analysis

Multiple linear regression has been used to test hypotheses H_1, H_2, H_4, H_6, H_8, H_{11} and H_{13} to determine the influence of Perceived Usefulness, Perceived Ease of Use, Trust, Government support, Perceived risk, Self-efficacy and Social Influence (Predictor or independent variables) on Attitude towards the FinTech services (Outcome or dependent variable). R square in regression helps in determining the total variability explained by the regression model. According to Cohen (1988) and Falk & Miller (1992) R square value of at least 0.10 i.e., 10 percent is considered acceptable. It has been noticed from the value of R square in regression analysis that 77.7 percent (R square = 0.777 in Table 5.23) variance in the dependent variable 'Attitude' has been explained by the predictor variables. Among the variables tested, Perceived Usefulness, Trust, Government support, Perceived risk and Social Influence are highly significant at 0.05 level of significance. Thus, it is found that the belief that FinTech services would help in the enormous improvement and enhance efficiency in conducting banking transactions positively influences attitude towards FinTech services. In addition, trust towards FinTech services, the support from the Government through the development of payment infrastructure, the promotion of digital payments through UPI and the influence from friends, relatives, etc. positively affect the attitude towards the use of FinTech services. The value of regression co-efficient (B) shows that for every one point increase in Perceived Usefulness, Trust, Government support and Social Influence, Attitude towards FinTech services is increased by 0.229, 0.263, 0.269 and 0.062 standard points (Table 5.23a) respectively. Furthermore, Perceived risk is found to have a negative influence on the Attitude towards FinTech services (p = 0.000, B = -0.097 in Table 5.23a). Thus, hypotheses H_1, H_4, H_6, H_8 and H_{13} has been supported.

Furthermore, Perceived Ease of Use and Self-efficacy does not have any significant impact on the Attitude towards FinTech services. Thus, hypotheses H_2 and H_{11} have not been supported at 0.05 level of significance (Table 5.23a). A plausible reason for this is the spur in the usage of FinTech services during the pandemic, as it has become a new necessity thereby resulting in a positive shift towards the attitude towards FinTech services, irrespective of whether a person has the efficacy to use it. It has been observed during the survey that many respondents especially Generation X and Baby Boomers seek help from their family members to make use of FinTech services to perform their financial transactions using FinTech.

Regression equation: Attitude (Y) = 1.165 + .229 (Perceived Usefulness) + .062 (Social Influence) - .097 (Perceived Risk) + .269 (Government Support) + .263 (Trust)

Table 5.23: Model Summary for H_1, H_2, H_4,H_6,H_8, H_{11}, H_{13}

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.882[a]	.777	.776	.47242	.777	528.041	7	1058	.000

a. Predictors: (Constant), TRU, SE, SI, PR, PEOU, GS, PU
b. Dependent Variable: ATT

Table 5.23a: Regression Coefficients for H_1,H_2,H_4,H_6,H_8,H_{11},H_{13}

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	1.165	.143		8.143	.000		
PU	.229	.024	.256	9.687	.000	.302	3.310
SI	.062	.014	.078	4.382	.000	.665	1.503
PR	-.097	.018	-.124	-5.522	.000	.418	2.390
GS	.269	.026	.257	10.490	.000	.351	2.846
SE	.010	.015	.014	.684	.494	.469	2.133
PEOU	.021	.017	.031	1.238	.216	.335	2.989
TRU	.263	.024	.286	11.044	.000	.313	3.199

a. Dependent Variable: ATT

Perceived Usefulness and Perceived Ease of Use are considered to be the prime determinants of using technology-based financial services. Consistent with the TAM model, the analysis reveals that Perceived Ease of Use has a significant positive effect on Perceived Usefulness (p = 0.000, B = 0.454 in Table 5.24a) thereby explaining 35.7 percent variance (Table 5.24) in Perceived Usefulness (R square = 0.357). Thus, H_3 has been supported. Therefore, it is concluded from the analysis that better the ease of use such as clear and understandable, easy to learn characteristics of FinTech-based services better is the usability i.e., increase in benefits felt in using FinTech services. The regression equation is

Perceived Usefulness (Y) = 2.782 + .454 (Perceived Ease of Use)

Table 5.24: Model Summary for H_3

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.598[a]	.357	.357	.89292	.357	591.463	1	1064	.000

a. Predictors: (Constant), PEOU

b. Dependent Variable: PU

Table 5.24a: Regression Coefficients for H_3

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	2.782	.059		47.268	.000
	PEOU	.454	.019	.598	24.320	.000

a. Dependent Variable: PU

It has been observed from Table 5.25a of the regression analysis that Government support (p = 0.000, B = 0.178) and Convenience (p = 0.000, B = 0.289) have a significant positive impact on Trust towards FinTech services. However, Perceived risk (p = 0.000, B = -0.157) has a significant negative influence on the trust towards FinTech services. Thus, H_5, H_7 and H_9 have been supported. Thus, it is concluded that the quick and easy method of payments, and the influencing role of the Government has fostered confidence among the respondents to use FinTech services and assisted in building trust. Besides, the Perceived risks such as cyber vulnerabilities and data breaches have a negative influence on the trust to use FinTech services. Consequently, navigating and addressing the risks would aid in lowering the potential risks and augment the trust in using digital financial services. Furthermore, offers given by the FinTech service providers do not have any significant impact on the trust towards FinTech services ($p = 0.486$). A possible explanation for this is that the resilience provided by FinTech services in performing banking transactions and initiatives taken by the Government in boosting FinTech services have narrowed down the effect of offers on trust towards FinTech services. Thus, H_{10} has not been supported. The regression equation

Trust (Y) = 2.635 + .178 (Government Support) - .157 (Perceived Risk) + .289 (Convenience)

Table 5.25: Model Summary for H_5, H_7, H_9,H_{10}

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.351[a]	.124	.119	.58807	.124	25.866	4	734	.000

a. Predictors: (Constant), Convenience, PR, Offers, GS

b. Dependent Variable: TRU

Table 5.25a: Regression Coefficients for H_5,H_7,H_9,H_{10}

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	2.635	.357		7.378	.000		
	GS	.178	.045	.143	3.906	.000	.897	1.115
	PR	-.157	.025	-.228	-6.337	.000	.926	1.080
	Offers	-.012	.017	-.025	-.697	.486	.948	1.055
	Convenience_	.289	.064	.159	4.523	.000	.968	1.033

a. Dependent Variable: TRU

Furthermore, the effect of Self-efficacy (a person's judgement about their capability of using FinTech services) on Perceived Ease of Use is also tested. The test results reveal that Self-efficacy has a significant direct effect on Perceived Ease of Use ($p = 0.000$, $B = 0.746$ in Table 5.26a) and explains 49.8 percent variance (R square = 0.498 in Table 5.26) in Perceived Ease of Use. Thus, hypothesis H_{12} has been supported. Hence, it is concluded that Self-efficacy is a crucial predictor of Perceived Ease of Use i.e., the respondents who can use FinTech services without any assistance from others consider the service to be more user-friendly. The regression equation is Perceived Ease of Use (Y) = 5.397 + .746 (Self-efficacy)

While examining whether the predictor variables Perceived Usefulness, Perceived Ease of Use, Social Influence, Self-efficacy and Attitude has a significant influence on the Behavioural Intention to use FinTech services. It has been observed from Table 5.27a that the independent variables, Perceived Usefulness (p = 0.000, B = 0.402), Perceived Ease of Use (p = 0.000, B = 0.144), Social Influence (p = 0.000, B = 0.101) and Attitude (p = 0.000, B = 0.549) has a significant positive influence on the Behavioural Intention to use FinTech services and explains 76.7 percent (R square = 0.767 in Table 5.27) variance on the dependent variable (Behavioural Intention). From the value of regression co-efficients (B), it has been observed that the attitude towards FinTech services has the highest level of influence on Behavioural Intention i.e., one point increase in the independent variable Attitude leads to 0.549 points increase in the Behavioural Intention to use FinTech services. Thus, H_{14}, H_{15}, H_{16} and H_{18} have been supported. Besides, Self-efficacy (p = 0.734) does not have any significant influence on the Behavioural Intention to use FinTech services. Therefore, H_{17} has not been supported. A possible explanation is that the less tech-savvy people try to seek the help of family members/relatives/friends to use the FinTech service, which narrowed down the effect of Self-efficacy on Behavioural Intention to use FinTech services. The regression equation is

Behavioural Intention (Y) = -.955 + .402 (Perceived Usefulness) + .144 (Perceived Ease of Use) + .101 (Social Influence) + .549 (Attitude)

Table 5.26: Model Summary for H_{12}

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.706[a]	.498	.497	1.03831	.498	1054.728	1	1064	.000

a. Predictors: (Constant), SE

b. Dependent Variable: PEOU

Table 5.26a: Regression Coefficient for H_{12}

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	5.397	.086		62.488	.000
	SE	.746	.023	.706	32.477	.000

a. Dependent Variable: PEOU

Table 5.27: Model Summary for H_{14}, H_{15}, H_{16}, H_{17}, H_{18}

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.876[a]	.767	.766	.63301	.767	698.724	5	1060	.000

a. Predictors: (Constant), ATT, SE, SI, PEOU, PU

b. Dependent Variable: INT

Table 5.27a: Regression Coefficients for H_{14},H_{15},H_{16},H_{17},H_{18}

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-.955	.127		-7.501	.000		
PU	.402	.031	.342	12.789	.000	.307	3.253
PEOU	.144	.023	.161	6.301	.000	.336	2.973
SI	.101	.019	.096	5.313	.000	.675	1.481
SE	.007	.020	.007	.340	.734	.479	2.088
ATT	.549	.033	.419	16.497	.000	.341	2.932

a. Dependent Variable: INT

Binary Logistic Regression has been used to examine whether the Behavioural Intention to use FinTech services (independent variable) significantly impacts the actual usage of FinTech services (dependent variable, dichotomous categorical variable where 'Yes' means the respondents use FinTech services and 'No' means that the respondents do not use any of the FinTech services). In Binary Logistic Regression, the Hosmer Lemeshow Test is a test for goodness of fit which requires the p value to be greater than 0.05. A small p value ($p < 0.05$) means that the model is not a good fit. In Table 5.28, Hosmer and Lemeshow Test indicate that the model is a good fit ($p = 0.730$). The predictor variable

Behavioural Intention explains 64 percent variance in actual usage of FinTech services (Nagelkerke R square = 0.640 in Table 5.29) and is significant but in the opposite direction (p = 0.000, B = -1.908 in Table 5.30). A tenable reason for this is that even though many respondents have a strong intention to use FinTech service but they have not yet started to use the service because they are comfortable using the conventional means of sending and receiving money. Especially the older generation and people with a low educational background because of their less tech-savvy nature have the fear of undertaking any mistake while performing transactions. However, they have a strong behavioural intention to use FinTech services in future with the help of their friends, relatives and the Common Service Centres [2]that are nearest to them. The regression equation is

Actual Usage (Y) = 6.214 – 1.908 (Behavioural Intention)

Table 5.28: The Hosmer and Lemeshow Test result

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	2.808	5	.730

Table 5.29: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	670.205[a]	.454	.640

Table 5.30: Regression result H_{19}

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	INT	-1.908	.130	216.208	1	.000	.148
	Constant	6.214	.514	146.417	1	.000	499.497

a. Variable(s) entered on step 1: INT.

5.3.4: Problems faced in using FinTech services

A five-point scale of agreement (interval scale) where 1 indicates 'least agreed' and 5 indicates 'most agreed' has been used to examine the problems such as service charges, connectivity issues, lack of awareness, cyber-security issues, etc. encountered by the respondents while utilising FinTech services.

[2] Common Service Centres (CSCs) are established under the Digital India Scheme. CSCs are the access points to provide utility services, welfare schemes, awareness about digital financial services and Government policies in rural and remote areas of the country.

Table 5.31: Problems that the respondents face in using FinTech services

Problems faced in using FinTech services (in %)	1	2	3	4	5
High service charges	59.4	13.0	9.6	12.3	5.7
Poor speed of internet	18.5	5.1	12.2	32.1	32.1
Unawareness	58.2	16.6	7.2	10.7	7.3
Transaction failure	25.8	6.0	10.8	31.5	25.9
Problem of hacking	49.7	12.4	7.7	15.0	15.2
Payment gets blocked and no confirmation is sent	46.0	16.0	13.8	15.7	8.5
Cumbersome navigation	61.6	19.6	4.9	9.7	4.2

Source: Field Survey

It is found that 32.1 percent of respondents have mostly agreed that they face the problem of poor speed of the internet followed by 25.9 percent of respondents who are concerned with the issue of transaction failure (Table 5.31). Thus, connectivity is posing constraints in the seamless use of technology-based financial services in the area of the study. In addition, 5.7 percent and 8.5 percent of respondents have mostly agreed that they face difficulty because of high service charges especially in using debit cards and payments being blocked and no confirmation being sent with regard to payment. Further, 7.3 percent of respondents are concerned with the issue of unawareness and 4.2 percent of respondents have mostly agreed that they consider the transaction process is cumbersome (i.e., have faced complications in using FinTech services due to unawareness). A little less than half of the respondents (49.7 percent) have not faced the problem of hacking but there is 15.2 percent of respondents, who have mostly agreed that they have faced cyber vulnerabilities while using FinTech services. This necessitates requisite efforts to combat the matter of cyber security to instill trust and eliminate the feeling of disquiet among bank customers in using FinTech services.

5.3.5: Problems faced in using FinTech services and demographic profile

This section aims to determine whether the problems that the respondents face in using FinTech services differ across the different demographic profiles. Independent samples t-test helps in comparing the means of two groups, thus, t-test has been used to find out whether the problems faced in using FinTech services differ across area of residence and gender.

5.3.5a: Problems in using FinTech services and area of residence

H_0: Problems faced in using FinTech services does not differ across the area of residence

H_1: Problems faced in using FinTech services differ across the area of residence

Table 5.32: Independent sample t test for problems faced in using FinTech services and area of residence

	Area of residence	**Mean**	**P value**
High service charges	Urban	1.85	0.452
	Rural	1.94	
Poor speed of internet	Urban	3.10	0.000
	Rural	3.64	
Unawareness	Urban	1.56	0.000
	Rural	2.01	
Transaction failure	Urban	2.98	0.016
	Rural	3.33	
Problem of hacking	Urban	1.97	0.001
	Rural	2.42	
Payment gets blocked and no confirmation is sent	Urban	2.39	0.191
	Rural	2.22	
Cumbersome navigation	Urban	1.49	0.000
	Rural	1.82	

From Table 5.32 it has been found that significant differences exist ($p < 0.05$) between the poor speed of the internet, unawareness, transaction failure, problem of hacking and the notion that the transaction process is cumbersome across the area of residence. Further, it has been observed from the mean values that the problems stated above are faced more in the rural areas than in urban areas. As the poor internet speed, transaction failure and cyber-frauds can negate the FinTech usage experience, thus, the problem of connectivity and cyber vulnerabilities especially in rural areas must be addressed.

5.3.5b: Problems in using FinTech services and gender

H_0: Problems faced in using FinTech services does not differ across gender

H_1: Problems faced in using FinTech services differ across gender

Table 5.33: Independent samples t-test for problems faced in using FinTech services and gender

	Gender	Mean	p value
High service charges	Male	1.89	0.227
	Female	2.07	
Poor speed of internet	Male	3.56	0.379
	Female	3.43	
Unawareness	Male	1.90	0.253
	Female	2.05	
Transaction failure	Male	3.28	0.444
	Female	3.16	
Problem of hacking	Male	2.37	0.149
	Female	2.16	
Payments gets blocked and no confirmation is sent	Male	2.26	0.666
	Female	2.20	
Cumbersome navigation	Male	1.73	0.294
	Female	1.86	

It is observed from the independent samples t test in Table 5.33 that there is no significant difference ($p > 0.05$) in the average problems faced in using FinTech services and gender. Thus, there is no sufficient evidence to reject the null hypothesis at 0.05 level of significance.

Further, One-Way Analysis of Variance (ANOVA), which compares the mean of three or more groups, have been used to determine whether the problems faced in using FinTech services differ across age and occupation.

5.3.5c: Problems in FinTech usage faced across different age group

H_0: Problems faced in using FinTech services does not differ across age group

H_1: Problems faced in using FinTech services differ across age group

Table 5.34: One-Way ANOVA for problems faced in using FinTech services and age

	Age group	Mean	p value
High service charges	18-28 years	1.64	0.000
	29-39 years	1.79	
	40-50 years	1.93	
	Above 50 years	2.33	
Poor speed of internet	18-28 years	3.50	0.479
	29-39 years	3.48	
	40-50 years	3.66	
	Above 50 years	3.46	

Unawareness	18-28 years	1.39	0.000
	29-39 years	1.45	
	40-50 years	2.19	
	Above 50 years	2.73	
Transaction failure	18-28 years	3.35	0.165
	29-39 years	3.34	
	40-50 years	3.29	
	Above 50 years	3.00	
Problem of hacking	18-28 years	2.22	0.686
	29-39 years	2.32	
	40-50 years	2.43	
	Above 50 years	2.30	
Payment gets blocked and no confirmation is sent	18-28 years	2.28	0.980
	29-39 years	2.27	
	40-50 years	2.23	
	Above 50 years	2.23	
Cumbersome navigation	18-28 years	1.36	0.000
	29-39 years	1.41	
	40-50 years	1.86	
	Above 50 years	2.49	

One-Way ANOVA Table 5.34, revealed that significant differences ($p < 0.05$) in terms of the problem of high service charges, unawareness and the belief that transaction process is cumbersome exist among the different age groups.

Post hoc analysis (Annexure K) also revealed that in terms of the problem of high service charges significant differences exist between the pairs 18-28 years and above 50 years, 29-39 years and above 50 years, 40-50 years and above 50 years. In terms of unawareness and cumbersome navigation, no significant difference exists between the pair 18-28 years and 29-39 years. However, significant differences exist between the pairs 18-28 and 40-50 years, 18-28 and above 50 years, 29-39 – 40-50 years and 29-39 – above 50 years.

Thus, it is concluded that the respondents above 50 years of age consider the service charges to be high. A possible explanation for this is that most of the respondents above 50 years of age mostly use debit cards which involve some charges on transaction limit, withdrawal and deposit in Cash Deposit Machines (CDM) and are not frequent users of UPI (zero charge-based FinTech service). In addition, mostly the respondents from the age group 40-50 years and above 50 years face the problem of unawareness in the use of FinTech-based applications and consider the steps of the transaction process to be lengthy.

5.3.5d: Problems encountered in FinTech usage across occupation

H_0: Problems faced in using FinTech services does not differ across occupation

H_1: Problems faced in using FinTech services differ across occupation

Table 5.35: One-Way ANOVA for problems faced in using FinTech services and occupation

	Occupation	**Mean**	**p value**
High service charges	Businessman/trader	1.61	0.000
	Agriculturist	1.94	
	Govt. service/PSUs	1.62	
	Private service	2.19	
	Self-employed/Professionals	1.68	
	Daily wage earner	2.42	
Poor speed of internet	Businessman/trader	3.57	0.591
	Agriculturist	3.70	
	Govt. service/PSUs	3.63	
	Private service	3.52	
	Self-employed/Professionals	3.43	
	Daily wage earner	3.26	
Unawareness	Businessman/trader	1.65	0.000
	Agriculturist	3.17	
	Govt. service/PSUs	1.81	
	Private service	1.84	
	Self-employed/Professionals	1.29	
	Daily wage earner	2.60	
Transaction failure	Businessman/trader	3.27	0.004
	Agriculturist	3.03	
	Govt. service/PSUs	3.56	
	Private service	3.32	
	Self-employed/Professionals	3.25	
	Daily wage earner	2.54	
Problem of hacking	Businessman/trader	2.17	0.129
	Agriculturist	2.34	
	Govt. service/PSUs	2.41	
	Private service	2.51	
	Self-employed/Professionals	2.11	
	Daily wage earner	2.06	
Payment gets blocked and no confirmation is sent	Businessman/trader	2.21	0.006
	Agriculturist	2.27	
	Govt. service/PSUs	2.56	
	Private service	2.24	
	Self-employed/Professionals	2.30	

	Daily wage earner	1.62	
Cumbersome navigation	Businessman/trader	1.60	0.000
	Agriculturist	2.69	
	Govt. service/PSUs	1.86	
	Private service	1.62	
	Self-employed/Professionals	1.24	
	Daily wage earner	2.10	

It is observed from Table 5.35 that there is significant difference ($p < 0.05$), between high service charges, unawareness, transaction failure, payments getting blocked and no confirmation being sent and cumbersome navigation across different occupations. It is found from the mean values that the constraints of unawareness and cumbersome navigation are mostly faced by agriculturists (3.17, 2.69), followed by daily wage earners (2.60, 2.10). This can be ascribed to the lack of digital literacy among such respondents. Transaction failure is the highest among Govt. service employees (3.56), private service employees (3.32) and businessmen/traders (3.27). As they are active users of FinTech services, thus, failure while performing financial transactions can lead to negative experiences in performing digital financial transactions. Furthermore, mostly daily wage earners consider the service charges to be high, a plausible reason for this is that the majority of the daily wage earners have debit cards which require payment of some charges and only a few use zero fee-based UPI apps thereby requiring the promotion of UPI based FinTech applications, especially among the daily wage earners.

Post hoc analysis (Annexure L) revealed that in terms of high service charges significant difference exists between daily wage earners and businessmen/traders, Govt. service employees. In terms of unawareness, payment being blocked and no confirmation being sent there is no significant difference between daily wage earners and agriculturists. However, significant differences exist between daily wage earners and other occupational groups, agriculturists and other occupational groups. In terms of transaction failure, there is significant difference between the following pairs i.e., Govt. service employees and agriculturists, daily wage earners and businessmen/traders, Govt. service employees, private service employees and self-employed professionals.

5.4: Chapter Summary

The empirical results reveal that the majority of the respondents are aware of third-party payment apps such as Google Pay and PayTm followed by UPI-based BHIM app. In terms of awareness about lendingtech and insurtech the awareness is particularly low, only 13 percent of respondents are aware of Lendingkart and a little less than half of the respondents are aware about policybazaar. Among 69.3 percent of respondents who use

FinTech services, the majority of them use Google Pay, internet banking with cent percent being users of debit cards. In addition, 64.7% of the respondents revealed that they have used FinTech services more frequently amidst the pandemic, which shows the increased embracing of digital financial services among respondents.

The examination of socio-demographic data with FinTech usage showed that there exists a very strong association between age, occupation, educational qualification, social group and use of FinTech services. Furthermore, digital financial services in the study area are mainly used for money transfers, recharges, in-person buying, and online shopping. However, the use of FinTech services for payment of utility bills including payments of fees at schools/colleges is found to be low. With regard to factors influencing the use of FinTech services, the results of the regression analysis showed that the perception of usefulness, trust, government support and social influence all significantly influence attitudes toward FinTech services.

Government support is crucial in promoting trust and growing confidence in FinTech services. This can be ascribed to the development in terms of payment infrastructure, the launch of the Unified Payment Interface, Aadhaar Enabled Payment System, the Digital India Initiative and network externalities such as influence from friends, relatives, etc. Although self-efficacy is a key predictor of perceived ease of use, attitudes and intentions to utilise FinTech services are not affected by it.

Furthermore, the attitude toward FinTech services is negatively impacted by perceived risk, such as vulnerability to cyberattacks, loss of financial and personal information, and technical difficulties during a transaction. Perceived risk is also found to have a negative influence on trust towards digital financial services.

Connectivity issues such as poor speed of the internet, transaction failure together with cyber vulnerabilities faced by the respondents create challenges in the seamless use of technology-based financial services. The independent samples t-test results showed that there is significant difference in terms of the issues such as unawareness, transaction failure and poor speed of internet and area of residence, as such issues are faced more in the rural areas than in the urban areas of the study. Furthermore, agriculturists, daily wage earners, and respondents from the age category 40 years and above mostly face the problem of unawareness and consider the transaction process to be cumbersome, which calls for increasing digital literacy to bridge the digital gap.