International Journal of Contemporary Business Research
Volume 1, Issue 1_2022

Factors Affecting Fintech Acceptance in Sri Lanka

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How to cite this paper:

Piyananda, D., Aluthge, C. (2022). Factors Affecting Fintech Acceptance in Sri Lanka. *International Journal of Contemporary Business Research 1*(1), 100–139.

ISSN Online: 2961 – 547X
ISSN Print: 2961 – 5259

Received: 12.02.2022
Accepted: 20.11.2022

Abstract

The purpose of this research is to identify the factors that affect consumers' Fintech acceptance in Sri Lanka. Based on the theory of Scenarization of Finance and some of the models developed in the information system field such as the Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, and Risky Technology Adoption models digital accessibility, digital capability, convenience, social influence, personal innovativeness, security concerns, and price value variables were selected as the significant variables for the proposed research framework. Structural Equation Model was used as a statistical test with SmartPLS software. The data source in this research is 440 primary data collected from Fintech banking services consumers. The results of the statistical analysis demonstrated that the level of scenarization of finance, measured in terms of digital accessibility, digital capability, and ease of use is a key concern when determining the adoption intention of Fintech services. Further, both social influence and price value have a significant negative impact while personal innovativeness creates a significant positive impact on consumers' adoption intention. Also, the study revealed that security concerns are having a negative impact, but the impact is not significant in the Sri Lankan context.

Keywords: Fintech, adoption intention, TAM, UTAUT, RAT, Scenarization of finance

1. Introduction

Fintech is the ellipsis for Financial Technology, which implies the application of innovative technologies in financial services (Vives, 2017). During the early ages of Fintech evolution (Fintech 1.0 and Fintech 2.0) financial institutions were in the position to adopt technology-driven applications. However, after the global financial crisis in 2008, Fintech 3.0 era fostered significant threats to incumbent players. This is because of the tightening regulatory requirements on banks through imposing increased capital requirements and reshaping the structure of banks as a proactive measure against the risk of repeat crisis in the future. As a result, banks had to pay more attention to these compliances. During this time innovation became a distinct priority. Accordingly, numerous game-changing technologies, such as WhatsApp, Air BnB, Facebook, Amazon, Google Pay, Apple Pay, Alipay, etc. became part of our day-to-day life. These innovative business models are more focused on providing customers with a better user experience (Hu, Ding, Li, Chen & Yung, 2019). As a result, customers were much adapted to the convenient services offered by these innovators, and they also expected the same level of services from the banks too. Berberis et al., (2015), argued that due to the collapse of trust and the regulatory reforms, banks were surprised by the unintended consequences of the rise of new technology-driven players as banks had limited capacity to compete with them.

Since 2015, Fintech services have seen an increase in awareness as well as adoption[2] globally (EY Fintech Adoption Index, 2019). In 2015, the year in which the first EY Fintech adoption index was published, the global Fintech adoption rate stood at 16%. Then the rate increased to 33% in 2017 and 64% in 2019. Further, 96% of global consumers are aware of at least one alternative Fintech service available and, 3 out of 4 global consumers use a money transfer and payments Fintech service (EY Fintech Adoption Index, 2019). Thus, although there are numerous Fintech applications available in the market, we can see a selective adoption of these services. This argument can be further supported through the data presented in Table 1 below.

[2] **Fintech Adoption** is used here to refer to the widespread use of a new application, product or process (Frost,2020).

Table I: Fintech Categories Ranked by Adoption Rate

Fintech Category	**Adoption Rate**		
	2015	**2017**	**2019**
Money transfer and payments	**18%**	**50%**	**75%**
Savings and investments	17%	24%	48%
Budgeting & financial planning	8%	20%	34%
Insurance	8%	10%	29%
Borrowing	6%	10%	27%

Source: EY Fintech Adoption Index, 2019

Accordingly, money transfer and payment services are driving the increase in the global Fintech adoption with 75% of consumers. When considering the other products, the adoption rate is at a low percentage, even below 50%, which indicates that the potential barriers to adopting Fintech services exist. Further, a significant gap between consumer awareness of Fintech products and their intention to adopt was investigated by a survey carried out by CGI Group Incorporation in 2016. Accordingly, they found that only an average of 72% of consumers are aware of Fintech with an average of 33% of consumers reporting current and planned behavioral intention to adopt Fintech services. This, big drop between awareness to expected usage validates that both incumbent players and new startups of the industry must pay more attention to convincing their products even for the interested customers to move from awareness to adoption.

Several scholars have investigated the uneven Fintech adoption patterns across different countries, for example, Frost (2020); Buckley & Webster (2016). This is because in developing countries a significant proportion of the population is still unconnected mainly due to the lack of digital infrastructures and digital literacy skills. Thus, they are reluctant to adopt digitally-driven financial solutions. Further, more potential can be seen in developing countries for Fintech due to the unmet demand for financial services. This is because the majority in developing countries are excluded from the formal financial system. Sri Lanka as a developing country is still in its infancy in adopting Fintech into its financial services sector. However, huge potentials exist for Fintech startups to leverage their business in Sri Lanka as the majority of the rural population is excluded from the formal financial system. The establishment of a business presence in the country is challenging for the startups as there is a lack of evidence-based assessments available for them regarding the important aspects that they shall consider when promoting their product to the majority who lacks digital literacy and digital infrastructure. Extant literature mainly focuses only on online banking, mobile, banking, etc. For example: Ashfa, Fernando and Yapa 2020; Jayasiri, Gunawaradana, and Dharmadasa, 2016. Thus, this study aims at uncovering the important factors which drive the consumers' Fintech adoption intention in Sri Lanka.

2. Literature review

The survey results of eminent consultancy firms have revealed that the rate of 'Fintech Adoption' varies across the countries significantly (For example, EY Fintech Adoption Index (2019), PWC Global Fintech Survey (2017)). Adoption is referring to reflecting the extensive use of new applications products or processes. King and Nesbitt (2020), also confirmed that Fintech is being adopted across markets worldwide unevenly. In their analysis they highlighted that in developing countries adoption is driven by unmet demand for financial services and in other economies, adoption can be related to high costs of traditional finance services, supportive regulatory environment, and other macroeconomic factors.

Previous researchers have applied different models developed in the information system field to explain the factors that influence the adoption of technology both at individual and organizational levels (Abbasi et al, 2015; Abu Tair &. Abu-Shanab, 2014; Venkatesh & Zhang, 2010). These models include; Theory of Reasoned Actions (TRA) (Fishbein & Ajzen, 1975), Social Cognitive Theory (SCT) (Bandura, 1986), Technology Acceptance Model (TAM) (Davis, 1989; Davis, Bagozzi & Warshaw, 1989), Theory of Planned Behavior (TPB) (Ajzen, 1991), The model combining TAM and the Theory of Planned Behavior (Taylor & Todd, 1995), Innovation Diffusion Theory (IDT) (Rogers, 1995), Motivational Model (MM) (Davis, Bagozzi & Warshaw, 1992), Extended TAM (Venkatesh & Davis, 2000), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003). However, selecting the best model among these multiple models which can fulfill the specific requirements of a study is considered a challenging choice to make (Venkatesh *et al.*, 2003). Cao (2016), applied only four models including TAM, MM, UTAUT, and Risky Technology Adoption Model (RTA), in identifying the factors that affect Fintech adoption intention in Finland.

Chen (2016), explains that the massive growth of Fintech adoption in Asia has resulted due to the phenomenon called 'Scenarization of Finance' which elaborates on the concept of integration between finance and real-life needs. Accordingly, he highlighted that the purpose of technology is not to make finance better but to make finance serve real-life better. China being one of the most progressive countries in the world in terms of Fintech growth has achieved this success merely through integration between technology and real-life needs. Chen (2016), has initiated the concept of scenarization of finance through deeper analysis of the Fintech success story of China. Moshirian et al. (2019), also stressed that extensive adoption of Fintech can be seen in Asia merely due to the fact of better integration between Fintech and real-life scenarios. For example, the success story of M-Pesa in Kenya can be used as the benchmark in identifying the potential for Fintech firms to raise living standards in developing nations (Yermack, 2018). The critical success factor of M-Pesa is that it operates with a law tech Fintech services which suitably meet the needs of customers who have a basic mobile phone that can send text messages. Thus, the story of M-Pesa further confirms that Fintech service providers in developing nations shall more focus on catering their services to the basic requirements of the potential consumers. Buckley & Webster (2016), also concluded that M-Pesa leverages existing infrastructure to deliver the simplicity and accessibility required of Fintech offerings in developing countries. McCaffrey & Schiff (2017), highlighted that success of Fintech firms in developing countries is determined through how well they can meet the needs of the broad number of poor and working-class citizens, whose day-to-day finances are often characterized by volatility, complexity, and improvisation. As a result, Fintech firms shall focus on establishing a reliable electrical grid that permits a broad consumer base to connect via mobile phones or the internet and the products shall be designed with simplicity and low cost.

Generally, the concept of scenarization of Finance captures the ability of Fintech services to generate a satisfied consumer base. Consumer satisfaction can be achieved by making available Fintech services for everyone. Simply, it is the 'accessibility' or reach to the financial services. Even though consumers are having access to the finance they might not be satisfied if they are incapable of using the services. This is mainly due to the lack of digital literacy among the people. Thus, to adapt to the innovative technology-driven applications in the financial services industry people should be better equipped with the required 'digital capabilities. Moreover, though consumers have access to finance, and they are capable to use them they are never satisfied if those products do not make their life easier. Thus, yet another important aspect is 'convenience'.

H_1: Digital Accessibility has a significant positive impact on the level of Scenarization of finance

H_2: Individuals' digital capability has a positive impact on the level of Scenarization of finance

H_3: Usefulness of Fintech services has a positive impact on the level of Scenarization of finance

H_4: The level of Scenarization of finance has a positive impact on an individual's Fintech adoption Intention.

Social Influence (SI): Social influence is considered an important dimension that affects an individual's adoption intention. The behavior of a role model or an important person in society influences the individual to adopt the new system (Venkatesh et al., 2003). Due to the uncertainty and risk associated with Fintech products, consumers naturally tend to look for other peoples' views and intentions on similar products. There are various studies which investigated a significant relation established between social influence and its effect on behavioral intention to use (Rahi et al., 2019; Alalwan et al., 2017; Rodrigues et al., 2016; Slade et al., 2015; Tan et al., 2014; Venkatesh et al., 2011). Kim et al. (2018) find social influence positively affects the intention to use a payment authentication system based on biometrics; Moon and Hwang (2018), show that social influence positively affects the intention to use crowdfunding. Further, the significant impact of social influence on digital banking adoption is confirmed by several scholars in Sri Lanka (Chandrasiri & Karandakatiya, 2018; Jayasiri, Gunawaradana, and Dharmadasa, 2016). When the potential consumers become more careful in adopting Fintech products, the same behavior may be emulated by the individuals to show the social influence on them.

H_5: Social influence has a positive impact on users' adoption intention.

Security Concerns (SC): SC was incorporated into the model by referring to the Risky Technology Adoption (RTA) model. When consumers suffer from expectation loss due to security concerns, Fintech product adoption may be delayed or rejected completely. Several previous scholars have asserted that risk-taking behavior differs greatly across individuals, across countries, across domains, and over time (For example; Dohmen et al., 2011; Falk et al., 2018; Fisher and Yao, 2017; Mata et al., 2016). Some individuals, especially from developing countries are scared of being targets for fraudulent attacks and as a result, they are still using cash excessively for their payments (Jones, 2018). Thus, both incumbent and new startups shall pay more attention to building consumer confidence and resulting market confidence as it is critical to establish technology-driven financial service products.

H_6: Security concern has a negative impact on users' adoption intention

Price Value: According to Venkatesh et al. (2012), and Dodds et al (1991), the price value means the consumers' cognitive trade-off between the perceived benefits and the monetary cost of a given Fintech product. Several other studies conducted in the Marketing field have revealed how the perceived price value improves the consumers' intention to buy products (see, for example, Grewal, Monroe, and Krishnan, 1998). Though some studies have found out less sensitivity of affluent consumers on the price of the Fintech products (for example, Wu & Wang, 2005), a substantial amount of many other studies conducted in diverse fields confirm the positive relationship between the cost-benefit of a product and behavioral intention to adopt (for example, Pura, 2005; Wu & Wang, 2005). When this is applied to the digital financial industry, it is evident that consumers are more concerned about transaction costs such as stamp duty, the interest cost, late payment charges, and all other types of service charges. Consumers seem very satisfied with Fintech products that deliver them the most advantageous combination of cost and benefit. Accordingly, the following hypothesis is proposed.

H_7: Price value will have a positive influence on users' adoption intention

Personal Innovativeness (PI)

PI is the degree to which an individual is relatively early in adopting a new idea than other members of a social system (Rogers and Singhal, 2003). Connor, Heavin and Donoghue (2016), define PI as the extent to which a person's predisposition or attitude reflects his or her tendency to experiment with new technologies independently of the communicated experience of others. Zarmpou, Saprikis, and Vlachopoulou (2010), conducted a survey in Greece with the participation of 445 respondents and investigated that PI was verified to have the strongest effect on mobile service adoption intention. As part of their research, Jhone et al. (2006), found that PI was positively related to technology infusion. That is because users who infuse any technological solution are required to use all appropriate applications for both intended and unintended purposes. Thus, lack of innovativeness among individuals may restrict them from experimenting with novel technology and thereby gaining additional insights. Further, Eastlick, Lotz and Warrington (2006), has been empirically tested a link between PI and electronic shopping as more innovative people are more likely to purchase online than those who are less innovative. Therefore, the next hypothesis can be specified as,

H_8: Personal Innovativeness (PI) has a positive influence on users' adoption intention.

3. Methodology

This research applies a quantitative approach to investigate the factors affecting Fintech acceptance in Sri Lanka. The data collection is based on the structured questionnaires distributed through Google Forms. A Likert 5-point scale was applied to all these questions with "1=Strongly Disagree", "2=Disagree", "3=Neither Agree nor Disagree", "4=Agree", "5=Strongly Agree".

Table 2: Operationalization of Variables

No.	Statement	References
	Digital Accessibility	

DA1	I am having a strong internet connection at home or the place where I stay	Powhatan Broadband Survey, 2016
DA2	I am having required devices (personal computer, laptop, tab, Smart mobile device) to access digital banking products	Powhatan Broadband Survey, 2016
DA3	I am often facing connectivity issues when accessing the internet	Powhatan Broadband Survey, 2016
DA4	I am often accessing my bank account via my personal computer, laptop, tab, smart mobile device	Powhatan Broadband Survey, 2016
PEU	**Convenience: Perceived Ease of Use/Perceived Convenience**	
PEU1	I often become confused when I use the digital banking services.	Davis (1989)
PEU2	I find it easy to apply the digital banking services to do what I want to do.	Davis (1989)
PEU3	I make errors frequently when applying digital banking services.	Davis (1989)
PEU4	The Digital Banking Services are rigid and inflexible to interact with.	Davis (1989)
PEU5	Overall, I find the Digital Banking Services easy for me to use.	Davis (1989)
DC	**Digital Capability**	
DC1	I am having sufficient web searching skills to use digital banking products	Son (2015)
DC2	I am having sufficient level of computer literacy (Ability to work with to work with computers) use digital banking products	Son (2015)
DC3	I am having sufficient level of digital literacy (Ability to work with digital technologies) to use digital banking products	Son (2015)

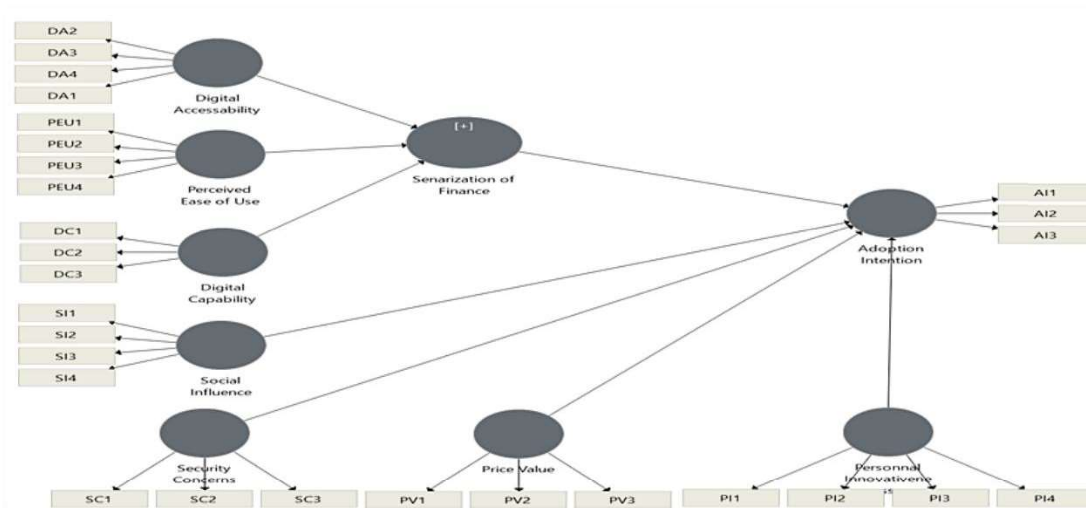
SI	**Social Influence**	
SI1	People who influence my behaviors think that I should use Digital Banking Services.	Venkatesh et al. (2012)
SI2	I am usually discussing the feeling of using Digital Banking Services with family and friends.	Wu, Tao & Yang (2008)
SI3	Most of my peers are using it, I should also use it.	Thompson et al. (1991)
SI4	People whose opinion that I value prefer that I use Digital Banking Services	Venkatesh et al. (2012)
SC	**Security Concerns**	
SC1	I feel secure to use Digital Banking Services	Gupta et al. (2010)
SC2	Security is the primary worry when considering to apply digital banking services.	Gupta et al. (2010)
SC3	Overall, I think digital banking services are safe for using	Gupta et al. (2010)
PV	**Price Value**	
PV1	I think service charges on digital banking services are reasonable.	Venkatesh et al. (2012)
PV2	I think digital banking services offer good value for money.	Venkatesh et al. (2012)
PV3	At the current price digital banking Services offer a good value.	Venkaresh et al. (2012)
PI	**Personal Innovativeness**	
PI1	I like to experiment with new information technologies	Agarwal et al. (1998)
PI2	Among my peers, I am usually the first to explore new information technologies.	Agarwal et al. (1998)
PI3	If I heard about a new information technology, I would look for ways to experiment with it.	Agarwal et al. (1998)

PI4	It will be easy for me to become skillful at using digital banking services.	Agarwal et al. (1998)
AI	**Adoption Intention**	
AI1	I plan to use Digital Banking Services in the future.	Rosen (1996)
AI2	I intend to use Digital Banking Services in the future.	Rosen (1996)
AI3	I predict I would use digital banking services in the future.	Rosen (1996)

Source: Author Compiled

In the present study, the sample includes Fintech banking consumers who use the wider range of Fintech services offered by banks including internet banking, mobile banking, digital wallets, digital financial planning, digital rewards and loyalty program, non-internet-based phone banking, and digital relationship manager. A total of 500 questionnaires was distributed among digitally active customers of selected banks out of which 440 complete responses were received. The sample size is a key issue when conducting Structural Equation Modelling (SEM). Both Kenny and McCoach, (2003) and Hair (2007) proposed that 15 responses per parameter are an appropriate ratio for sample size. Applying the same approach this study reached 440 respondents to measure 29 parameters.

Structural Equation Modelling (SEM) was applied for hypothesis testing. SEM is considered a standardized method in research when analyzing the cause-effect relations between latent constructs (Hair, Ringle & Sarstedt, 2011). This research uses the PLS-SEM to validate the measurement and hypothesis testing. PLS-SEM uses a regression approach that minimized residual variance from internal construct and is proven as more powerful with fewer issues when compared to CB-SEM, PLS-SEM (Hair et al.,2014). PLS-SEM works with large and small samples and is able to include and combine formative and reflective constructs (Hair et al.,2014). The validity tests were conducted to establish the validity of the questionnaire items. This research uses three tests as the criteria to confirm the convergent and discriminant validity of the measurement items: 1) All factor loading must exceed the 0.5 cutoff point. 2) All average variance extracted (AVEs) must be higher than 0.5 3) Square root of AVEs and other inter-construct correlations is compared to assess the discriminant validity. The square root of the Average Variance Extracted (AVEs) of each construct has to be higher than the correlations between it and any other constructs. The reliability of the measurements was evaluated using the composite reliability scores. The reliability score is adequate if exceeds recommended threshold point of 0.70 (Nunnally,1978).



Source: Smart PLS output

Figure 1: Path Diagram

4. Results and discussion

4.1. Demographic Profiles of the Respondents

The demographic and background data collected included age, gender, educational level, marital status, occupation, monthly income, and the type of digital banking services used. The main purpose of descriptive analysis is to understand the profile of the respondents. Table III below shows the summary of the descriptive analysis.

Table 3: Profile of the Respondents

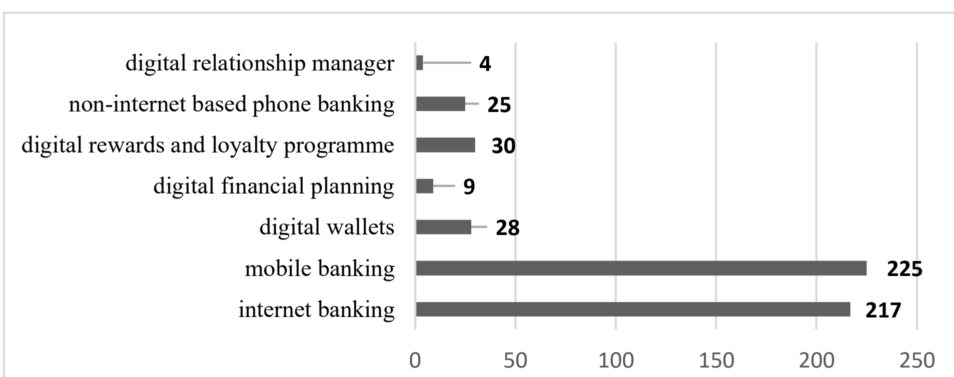
Age Group	No. of Respondents	Percentage of Respondents
18-24	142	33%
25-34	189	44%
35-44	56	13%
45-54	12	3%
55-64	17	4%
Above 65	12	3%
Gender		
Male	189	44%
Female	239	56%
Education Level		
GCE AL/OL	13	3%
Diploma/Higher Diploma	142	33%
Undergraduate	145	34%
Graduate	128	30%
Occupation		
Executive, Trainees, Assistants	265	62%
Senior Management Positions	163	38%
Income Level		
Less than Rs.50,000	164	38%
Rs.50,001 – Rs.100,000	78	18%
Rs.100,0001 – Rs.150,000	68	16%
Rs.150,001 – Rs.200,000	48	11%
Rs.200,001 – Rs.250,000	27	6%
Above Rs.250,000	43	10%

Source: Survey Results

Survey results highlighted that young people tend to adopt tech-savvy financial services than the older generation as the majority (77%) were in the 18–35-year age group followed by the 13% in the 35–44-year age group, and 10% above 45-year age group. In this study, there are a total of 239 (56%) female respondents and 189 (44%) male respondents. The percentage shows that the female respondents are much higher than the male respondents. The majority (64%) of respondents are well educated as they are following a degree or having a degree. In addition, 33% of the total respondents are having a Diploma or Higher Diploma qualification and a lesser percentage (3%) of the respondents are having basic education like passing GCE A/L or O/L. The majority of respondents (more than 60%) are employed in trainee and executive levels and the rest of the respondents are occupied in senior management positions. Fixed income earners usually tend to apply digital banking services as all the respondents are fixed income earners. In the monthly income segment, most of the respondents have an income of less than Rs. 50,000 which was 164 respondents (38%). Followed by the income group of Rs. 50,001 – Rs. 100,000, with 78 respondents (18%). Ranked third is Rs.100,001- Rs. 150,000, with 68 respondents (16%) having a high income; 48 respondents (11%) have a higher income of between Rs.150,001- Rs.200,000 and 27 respondents (6%) are from the earnings group between Rs.200,001 and Rs.250,000. Further, 43 respondents (10%) are representing the highest income group of above Rs. 250,000.

4.2. Most frequently used digital banking applications

The survey results indicate that all the respondents are using either internet banking



or mobile banking and only a few respondents are using innovative applications in digital banking such as digital wallets, digital financial planning, digital relationship manager, etc. As shown in the following Figure 4.1 only a few respondents are using the new applications offered by the banks under their journey of digitalizing the services. As a developing country, Sri Lanka is still at its early stage of Fintech adoption, and as a result, currently, consumers prefer mobile banking and internet banking rather than the novel applications of Fintech in banking services.

Source: Survey Results

Figure 2: No. of Users of Different Digital Banking Services

Under the measurement model analysis, the reliability and validity of the constructs were assessed in terms of their content validity, reliability, convergent validity, and discriminant validity (Gefen & Straub, 2005; Hair et al., 2013; Hulland, 1999). First, the reliability of the constructs was assessed. The Reliability Analysis calculates several commonly used measures of scale reliability and provides information about the relationships between individual items in the scale. Cronbach's Alpha (CA) and Composite Reliability (CR) are the most used reliability measure for questionnaires with multiple scales (Fornell & Larcker, 1981; Hair et al. 2006; Nunnally & Bernstein, 1994).

4.3. Test for reliability and validity of constructs

Table 4: Internal Reliability and Convergent Validity of the Measurements

	Cronbach's Alpha (CA)	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI	0.904	0.904	0.940	0.838
DA	0.697	0.502	0.798	0.665
DC	0.665	0.729	0.810	0.591
PEU	0.863	0.880	0.910	0.722
PI	0.842	0.902	0.896	0.691
PV	0.772	0.766	0.803	0.583
SC	0.780	0.828	0.868	0.688
SF	0.763	0.864	0.721	0.506
SI	0.762	0.762	0.894	0.808

4.3.1. Composite Reliability (CR)

As per Netemeyer (2003), CR is an alternative measure for CA to measure the construct reliability. In general, social science research evaluates that the variables are reliable when either the CA or CR value exceeds 0.7 (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). Most scholars preferred CR as a measure of true reliability as CA sometimes over or underestimates the scale reliability (Eliakunda, 2019). As a measure of reliability, CR varies from 0 to 1, and the value of '1' indicates the perfect estimated reliability (Hair et al., 2017). According to Chin (1998), CR should be equal to or greater than 0.6 while according to Henseler et al., (2012), CR should be equal to or greater than 0.7 and equal to or greater than 0.8 is considered good. As shown in Table IV above CR values for each latent variable range from 0.798 to 0.940. Therefore, the CR of the constructs of this study is established as all the values are above 0.7.

4.3.2. Convergent Validity (CV)

CV assesses the validity of the questionnaire to measure what it is intended to measure for the latent variable (Hair, et al., 2017). Before running PLS Algorithm, both convergent and discriminant validity should be established (Saunders et al., 2015). CV is assessed based on the Average Variance Extracted (AVE). When the AVE is equal to or higher than 0.5, the CV is proven (Chin and Todd, 1995; Fornell & Larcker, 1981; Hair et al., 2006). AVE value equal to or greater than 0.50 explains that more than half (1/2) of the variance of the indicators is defined by the construct on average. On the other hand, an AVE less than 0.5 demonstrates that the error term of the indicator contains more variance than what is explained by the construct. As per the data presented in the above Table IV, AVE at reflective scales for all the latent variables are above 0.5. Thus, the CV for each construct of this study is established.

4.3.3. Discriminant Validity (DV)

DV assesses the extent to which a construct differs from other constructs, by assessing the correlation between constructs (Saunders et al.,2015). Also, Andreev et al., (2009) stated that DV assesses whether indicators of latent variables are not related to each other as per the theoretical expectation. Kline (2011), claimed that to establish the DV among constructs their inter-correlation should be at a lesser value. There are a few ways that can be applied in assessing the DV including cross-loading of indicators, Fornell and Larcker criterion, and Heterotrait-monotrait (HTMT) ratio of correlation. Among these methods, Fornell and Larcker criterion is the commonly used method while the heterotrait-monotrait (HTMT) ratio of correlations method is a new method that emerged for this purpose. Thus, both Fornell and Larcker criterion and HTMT method are employed in this study to ensure the DV between constructs.

Table 5: Discriminant Validity - Fornell-Larcker Criterion

	AVE	AI	DA	DC	PEU	PI	PV	SC	SF	SI
AI	0.838	**0.916**								
DA	0.665	0.408	**0.815**							
DC	0.591	0.215	0.102	**0.769**						
PEU	0.722	0.489	0.630	0.184	**0.849**					
PI	0.691	0.790	0.426	0.231	0.519	**0.831**				

PV	0.583	0.652	0.432	0.543	0.431	0.672	**0.754**			
SC	0.688	0.206	0.230	0.133	0.182	0.225	0.165	**0.829**		
SF	0.506	0.521	0.589	0.341	0.555	0.552	0.432	0.228	**0.637**	
SI	0.808	0.324	0.268	0.228	0.303	0.358	0.113	0.296	0.346	**0.899**

Source: Smart PLS output

The DV was assessed using Fornell and Larcker (1981) by comparing the square root of each AVE in the diagonal with the correlation coefficients (off-diagonal) for each construct in the relevant rows and columns (Hair et al., 2014). Therefore, the square root of each construct's AVE should have a greater value than the correlations with other latent constructs. As per the statistics presented in above table V the square root of the AVE of each latent variable (in bold) is higher than other correlations among the constructs. Therefore, the DV is established as per the Fornell-Larcker criterion.

Table 6: Discriminant Validity - Heterotrait- Monotrait ratio (HTMT)

	AI	**DA**	**DC**	**PEU**	**PI**	**SC**	**SF**	**SI**
AI								
DA	0.611							
DC	0.282	0.158						
PEU	0.556	0.876	0.234					
PI	0.102	0.674	0.333	0.636				
PV	0.436	0.234	0.632	0.253				
SC	0.234	0.351	0.172	0.223	0.283			
SF	0.614	0.169	0.776	0.071	0.701	0.294		
SI	0.390	0.437	0.324	0.383	0.481	0.388	0.478	0.321

Source: Smart PLS output

When applying HTMT to establish the DV, calculated HTMT values are to be compared with a pre-specified threshold. Accordingly, a lack of DV can be seen when the HTMT values are higher than the said threshold. Kline (2011), suggested a threshold of 0.85. In addition, Gold et al., (2001), proposed a value of 0.9. Table VI above showed the output from the HTMT analysis and based on the HTMT data presented, it is confirmed that no DV problems are according to the $HTMT_{0.9}$

criteria. Thus, all the indicators of latent variables were measuring different latent constructs. Thus, the model does not contain any overlapping indicators from the respondents' perceptions. All in all, it can be concluded that all the constructs of this study have confirmed the DV (Fornell & Larcker, 1981).

4.4. Main model estimation (pls-sem)

4.4.1. Structural Model (Inner Model)

The researcher applied the five steps suggested by Hair et al. (2017) to assess the structural model results in this section.

Step 1: Assess the structural model for Collinearity issues

Multicollinearity occurs when two or more predictors in the model are correlated and provide redundant information about the response. Multicollinearity between items is a significant issue in PLS-SEM as they influence the estimation of outer loading, weights, and their statistical significance (Eliakunda, 2019). This is because that multicollinearity raises the standard error and as a result affects the ability to differentiate the outer loading estimate to be different from zero. Hair et al. (2014) suggested assessing the multicollinearity of the constructs before deriving the structural model. Further, they recommended revising the model if any of the VIF values exceeded 5. Thus, before conducting model assessment researcher tested the structural model for multicollinearity. This is necessary as the estimation of path coefficients of this study is based on the Ordinary Least Square (OLS) regression (Hair et al., 2017). Both Variance Inflation Factor (VIF) and tolerance values were used to test multicollinearity problems for both independent variables and dependent variables. As per Mansfield & Helms (1982), multicollinearity problems do not occur when the VIF value is over 0.5 and multicollinearity is low when the tolerance value is close to 1. Some other scholars stated that a TOL value less than 0.2 or a VIF value above 5 can be treated as multicollinearity (For example, Hair et al., (2014), James et al., (2013). Hair, et al., (2017) claimed that if the level of collinearity value measured through TOL is 0.20 or lower and a VIF value of 5 or more, the researcher should consider eliminating one of a corresponding measured variables or combine the collinear measured variables into one or new composite measured variable or an index.

Table 7: Inner VIF and TOL values

	VIF (AI)	SIF (SF)	TOL (1/VIF)
DA		1.658	0.603
DC		1.036	0.965
PEU		1.699	0.588
PI	1.515		0.660
PV	1.432		0.734
SC	1.125		0.888
SF	1.503		0.665
SI	1.250		0.8

Source: Smart PLS Output

Data were tested for multicollinearity. Table VII shows that none of the constructs exceeded the recommended cut-off value of 5 for VIF and all the constructs' TOL value is in excess of the threshold of 0.2. Thus, multicollinearity was not a problem as the highest VIF value was 1.699 which is well below the expected threshold of 5. Further, TOL values were ranged from 0.58 to 0.96 which is well above the threshold value of 0.2. Thus, the author can conclude that there is no multicollinearity problem for independent variables and dependent variables.

Step 2: Significance and Relevance of the Structural Model Path Coefficients

After ensuring no multicollinearity exists in the structural model, the researcher assessed the significance and relevance of the path coefficients of the hypothesized relationships. 'T-statistics' generated using bootstrapping is used to evaluate the significance of the path coefficients. This step involves measuring and examining the structural model's predictive capabilities and the relationship between the latent constructs. In PLS-SEM, path coefficient can be used to assess the significance and relevance of the structural model relationships, R^2 value to assess the model's predictive accuracy, the model's predictive relevance can be established through Q^2. Further, f^2 can be used to evaluate the impact of independent variables on the dependent variable

Path Coefficients

In the structural model, the 'path analysis' method is applied to analyze the parameters **(**Mateos-Aparicio, 2011). Path coefficients are the values that appeared on the paths between latent variables in the structural model. Also, path coefficients reflect the direct effect of one independent variable on the dependent variable. For example, if a particular path coefficient was P, this means that an increase of 1 Standard Deviation in the exogenous Latent Variable would result in an increase of P in the Standard Deviation of the dependent variable (Har *et al*., 2014). Path significance of this model is assessed through bootstrapping procedure of SMART PLS 3.3.5. The significance of the path coefficients between the Latent Variables was examined referring to the t-values produced by bootstrap, and the direction of the relationship between latent variables was established referring to the algebraic sign of the path coefficients.

Table 8: Path Coefficients

Hypothesis	Relationship	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Result
H1	**DA->SF**	0.362	0.025	14.295	**0.000**	**Supported**
H2	**DC->SF**	0.132	0.044	2.989	**0.003**	**Supported**
H3	**PEU->SF**	0.707	0.022	31.793	**0.000**	**Supported**
H4	**SF ->AI**	0.015	0.009	2.694	**0.018**	**Supported**
H5	**SI->AI**	-0.022	0.010	2.254	**0.025**	**Supported**
H6	**SC ->AI**	-0.006	0.007	0.865	**0.388**	**Not Supported**
H7	**PV->AI**	-0.059	0.010	6.131	**0.000**	**Supported**
H8	**PI ->AI**	1.035	0.007	143.496	**0.000**	**Supported**

Source: SMART PLS Output

Hypotheses Testing

Depending on the various coefficient values and scores obtained from the analysis, the established hypotheses were tested according to the direction and strength of the path coefficients (β), 'T- statistics and significance level given by 'p value'. Statistical significance of structural paths was established using 'P-Value test'. Accordingly, to ensure that $\beta>0$, at the 0.05 significance level, the two-tailed P-value associated with the path coefficient was calculated. When $P\leq0.05$ the hypothesis is supported otherwise the hypothesis is not supported. The 'T ratio test' can be seen as a variation of this test, where the 'T-ratio' sometimes named as 't-statistic' or 'T-statistic' or P-value was used against a threshold of 1.96.

Digital Accessibility and the Level of Scenarization of Finance

H_1: Digital Accessibility has a significant positive impact on the level of Scenarization of Finance, (DA -> SF)

The path leading from digital accessibility to scenarization of finance was used to examine the hypothesized relationship (H1) which indicates a positive relationship between digital accessibility on measuring the level of scenarization of finance. The test for this hypothesis showed that digital accessibility was positively related to scenarization of finance ($\beta= 0.362$; Statistics =14.295; $p = 0.000$). This indicates that when digital accessibility increases by 1, the level of scenarization of finance goes up by 0362. Thus, the study showed that a higher level of digital accessibility would result in a greater level of scenarization of finance. Thus, the H1 of the study was supported.

Digital Capability and the Level of Scenarization of Finance

H_2: Digital Capability has a significant positive impact on the level of Scenarization of Finance (DC -> SF)

The study had established a significant positive relationship between digital capability and the level of scenarization of finance. The path leading from digital capabilities to scenarization of finance was used to examine this hypothesized relationship (H2). The test for this hypothesis showed that digital capabilities were positively related to the level of scenarization of finance ($\beta= 0.132$; T Statistics = 31.793; $p =0.003$), which indicates that when digital capabilities go up by 1, the level of scenarization of finance goes up by 0.132. Thus, the study showed that a higher level of process hard quality would result in a greater level of B2B multi-process cargo clearance. Thus, the H2 of the study was supported.

Perceived Ease of Use and Scenarization of Finance

H_3: Perceived Ease of Use of Fintech services has a positive impact on the level of Scenarization of Finance (PEU -> SF)

The test for this hypothesis showed that Perceived Ease of Use was positively related to scenarization of Finance ($\beta = 0.707$; T Statistics = 31.793; $p = 0.000$), meaning that when Perceived Ease of Use goes up by 1, scenarization of Finance goes up by 0.707. Thus, the study showed that a higher the Perceived Ease of Use offered by Fintech products greater the level of scenarization of Finance. Thus, the H3 of the study was supported.

Scenarization of Finance and the Users' Adoption Intention

H_4: The level of scenarization of finance has a significant positive impact on an individual's Fintech adoption intention (SF -> AI)

The test for this hypothesis showed that scenarization of finance was positively related to Users' Adoption Intention ($\beta = 0.015$; T Statistics = 2.694; $p = 0.018$), meaning that when scenarization of finance goes up by 1, Users' Adoption Intention goes up by 0.015 standard deviations. Thus, the study showed that a higher level of scenarization of finance would result in a greater level of users' Fintech adoption intention. Thus, the H4 of the study was supported.

Social Influence and the Adoption Intention

H_5: Social influence has a significant positive impact on users' adoption intention.

The test for this hypothesis showed that scenarization of finance was negatively related to Users' Adoption Intention ($\beta = -0.022$; T Statistics = 2.254; $p = 0.025$), meaning that when social influence goes up by 1, Users' Adoption Intention goes down by 0.022. Thus, the study showed that a higher level of social influence would result in a lesser level of users' Fintech adoption intention. Thus, the H5 of the study was supported.

Security Concern and Adoption Intention

H_6: Security concern has a negative impact on users' adoption intention (SC ->AI)

The test for this hypothesis showed that security concern was negatively related to adoption intention (β= -0.006; T Statistics = 0.865; p =0.388), meaning that when security concern goes up by 1, adoption intention goes down by 0.006. Also, since the p value is >0.05, the study showed no statistically significant relationship between security concerns and the users' Fintech adoption intention. Hence, the H6 of the study was not supported.

Price Value and the Adoption Intention

H_7: Price value will have a positive influence on users' adoption intention (PV->AI)

The test for this hypothesis showed that price value was negatively related to users' adoption intention (β= -0.059; T Statistics = 6.131; p = 0.000), meaning that when price value goes up by 1, users' adoption intention goes down by 0.059. Thus, the study showed that a higher level of price value would result in a lesser level of users' Fintech adoption. Thus, the H7 of the study was not supported.

Personal Innovativeness and Adoption Intention (PI ->AI)

H_8: Personal Innovativeness (PO) has a positive influence on users' adoption intention.

The test for this hypothesis showed that Personal Innovativeness was positively related to users' adoption intention (β= 1.035; T Statistics = 143.496; p = 0.000), meaning that when Personal Innovativeness goes up by 1, users' adoption intention goes up by 1.035. Thus, the study showed that a higher level of Personal Innovativeness would result in a greater level of users' Fintech adoption. Thus, the H8 of the study was supported.

Step 3: Coefficient of Determination (R^2 Value)

As a statistical measure coefficient of determination which denotes R^2 is an important criterion for a structural model. R^2 explains the model's predictive power or the extent of the percentage variation of the dependent variable explained by the independent variable/s. According to the recommendations of Cohen (1988), R^2 values of 0.26, 0.13, and 0.02 related to endogenous constructs might be interpreted as substantial, moderate, or weak respectively. Whereas as per Hair et al. (2017), R^2 values of 0.75, 0.50, or 0.25 for endogenous latent constructs can, as a rule of thumb, be correspondently described as substantial, moderate, or weak. Further, the improved version of the R^2 is the adjusted coefficient of determination (adjusted R^2). This is calculated by adjusting the coefficient for the number of predictors in the model.

Table 9: R^2 and Adjusted R^2 values

	R Square	**R Square Adjusted**
Adoption Intention	0.982	0.982

Source: SMART PLS Output

The examination of the endogenous variables' predictive power had high R^2 values (refer to Table IX). The explanatory power for Fintech adoption intention, the focal latent construct of this study is substantial (0.982) and therefore provides good support for nomological validity of the proposed research model.

Step 4: Results of Effect Size f^2

Effect size (f^2) was used to assess whether an omitted predictor latent construct had a substantive impact on the endogenous latent construct (Hair et al., 2017). Further, the f^2 values presented in Table 8 below explain the impact on the endogenous variable in the absence of that specific exogenous latent variable from the model. The results for the f^2 presented in Table X can be interpreted as the effect of dropping Digital Accessibility (DA) and Personal Innovativeness (PI) from the model has a high impact on the dependent variable. Further, dropping of Digital Capabilities (DC), Perceived Ease of Use (PEU), and scenarization of Finance (SF) is having a medium impact on the dependent variable. Also, the dropping of Security Concerns (SC) and Social Influence (SI) is having a small impact on the dependent variable.

Table 10: Effect Size

	AI	**SF**	**Effect Size**
DA		.656	Large
DC		.328	Medium
PEU		.338	Medium
PI	0.379		Large

SC	0.04		Small
SF	0.303		Medium
SI	0.036		Small

Note: If f^2 is <0.02 no effect; 0.02-0.14 small, 0.15-0.34 medium; >0.35 Large

Source: Smart PLS output

Step 5: Predictive Relevance Q^2

The predictive relevance of the model critically evaluates the predictive validity of a complex model (Stone, 1974; Geisser, 1975; Cha, 1994; Chin, 1998). The predictive sample reuse technique (Q^2) can be effectively used as a criterion for predictive relevance (Stone, 1974; Geisser, 1975; Cha, 1994; Chin, 2010). Therefore, based on the blindfolding procedure of Smart PLS, Q^2 values for each construct were calculated. The rule of thumb indicates that a cross-validated redundancy of above 0.5 ($Q^2 > 0.5$) can be regarded as a predictive model (Chin, 2010). However, Q^2 values larger than zero are meaningful, and values higher than 0, 0.25, and 0.50 depict respectively the small, medium, and large predictive accuracy of the PLS path model (Hair et al., 2018). Since Q^2 values presented in Table XI below are above zero, the researcher can confidently conclude that the model has predictive relevance. In other words, the model under study is relevant to predict the considered endogenous variable.

Table 11: Construct Cross-validated Redundancy

	SSO	SSE	Q^2 (=1-SSE/SSO)	Predictive Relevance
AI	984.000	179.442	0.818	Large
DA	1312.000	1312.000		
DC	984.000	984.000		
PI	1312.000	1312.000		
PV	984.000	984.000		
SC	984.000	984.000		

SF	3608.000	2361.827	0.345	Medium
SI	1312.000	1312.000		
USE	1312.000	1312.000		

Note: If Q^2 is 0.02-0.14 small, 0.15-0.34 medium; >0.35 Large

Source: Smart PLS output

5. Discussion

Study findings revealed that digital accessibility has a significant positive impact on the level of scenarization of Finance. This indicates that when people have more access to digital financial solutions those services will better serve individuals, businesses, and even the government. As per the study findings, usefulness of Fintech services resulted to establish a higher level of scenarization of finance. When Fintech products simplified the financial transactions, this will lead to making consumers' life easier. Consequently, when Fintech firms develop new products, they shall mainly focus on the consumer needs rather than digitalizing conventional business models which most of the incumbents do. Hence, they shall start the process of developing a new product as a solution to existing market issues. In the end, they should be able to make a real impact on the target market.

The findings of the study also confirmed that there is a statistically significant relationship between social influence and adoption intention. Zhou et al. (2010), reported a strong influence of social groups on consumers' adoption intentions. Also, the study finding is compatible with many of the previous studies for example, Baabdullah et al., 2019; Makanyeza, 2017; Malaquias & Hwang, 2019. As per Gbongli et al., (2019), when there is a high social influence from the reference group to which the individual belongs, a higher understanding of the usefulness of a new product/service is shown. Matsuo et al., (2018), highlighted that social influence is having a direct impact on adoption intention when users are having less experience with the technology. Therefore, people with less knowledge, less confidence, and less perceived utility can be motivated to adopt new technologies through their reference groups.

The direct relationship between personal innovativeness and Fintech adoption is evidenced in the study as it removes the resistance of an individual to use Fintech services while resolving their uncertainties regarding the applications of these services. According to Liebana-Cabanillas et al. (2018), highly innovative consumers can act as a pioneer for the implementation of new information technology. Further, innovative persons can help to measure and predict the behavior of the user and make a correction if any errors are found, and they are indicated as risk-takers with respect to the ambiguity of new technologies (Liebana-Cabanillas et al., 2018; Kosba et al., 2016).

As per the Expectancy Theory of Vroom (1964), there is a direct effect of perceived security on intention to use new technologies. Furthermore, as per the Privacy Calculus Theory, privacy risk directly and negatively affects privacy behaviors (Chellappa and Sin 2005; Dinev and Hart 2006). The findings of the study also confirmed a significant negative impact of security concerns towards Fintech adoption intention in Sri Lanka. Stewart and Jurjens (2018), highlighted that security threats with respect to mobile applications in Germany have been increased enormously and have become a key challenge for both users and Fintech firms. Therefore, service providers shall think of developing strategies to enhance consumers' knowledge and understanding of the services. Further, the firms shall take a license or a certificate from the government authority to conduct services like conventional service providers in order to build trust among consumers.

The findings of the study confirmed that there is a statistically significant positive relationship between price value and Fintech adoption intention in Sri Lanka. This finding is consistent with the past studies (Grewal et al., 1998; Pura, 2005). Thus, price value is an important concern for both incumbent players and Fintech startups when launching products in Sri Lanka.

6. Conclusion

Drawing on SEM the theoretical lens of the scenarization of finance and TAM, UTAUT, RAT models, this study assesses the combination of factors that significantly impact Fintech acceptance in Sri Lanka. To the best of our knowledge, this is the first study that empirically examines the concept of scenarization of finance in Fintech acceptance research. Thus, this study has addressed an important knowledge gap in the literature. In addition, this study extends research on Fintech acceptance that has predominantly been aligned to conventional theoretical models of the information system field. Given the complications in decision making on whether or not to use the technological innovations, this knowledge is critically important for research, practice and policy. The relevance of this study can be further extended by considering the new perspectives in future studies to examine the conditions to Fintech acceptance in other countries since the context has been identified as important even in the same country. In spite of the contributions, this study has a few limitations. First, the study utilized only the SEM methodology. Also, the researcher identified that most of the extant studies in this area are conducted using a quantitative approach and as a result, new inspiration to Fintech acceptance research, can be brought for future studies to qualitatively examine this phenomenon. Second, the study is limited to constructs of the scenarization of Finance, TAM, RAT, and UTAUT models, thus, future research can explore the configuration of other conditions that are not captured in this study. Lastly, the study was conducted in Sri Lanka, a developing country. Given that there are differences in the development and peculiarities between countries, a cross-country investigation between developed and developing countries could reveal further insights as well as stimulate a wider understanding of how Fintech acceptance can enhance those economies.

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