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Fintech Adoption Behaviour Among Accounting Professionals in Sri Lanka: An Analysis of User Types Before and After COVID-19

Saarankan, K., Kavinda, D.D.C*, and Wijesinghe, M.R.P

SAB Campus,
The Institute of Chartered Accountants of Sri Lanka.

Department of Business Finance,
University of Peradeniya.

Department of Finance
University of Kelaniya.

*chalithkavinda@mgt.pdn.ac.lk

ABSTRACT

The rapid evolution of Financial Technology (Fintech) has transformed how individuals and organizations conduct financial transactions, yet user adoption patterns remain underexplored in emerging economies such as Sri Lanka. In particular, the extent to which user characteristics influence the frequency, volume, and diversity of fintech usage before and after the COVID-19 pandemic remains unclear. Accordingly, the main objective of this study is to examine the impact of frequency, transaction volume, and application use of fintech on different user types. Primary data were collected through a structured questionnaire distributed online among accounting professionals in the Western Province of Sri Lanka during 2022, yielding 93 valid responses. The sample was selected using purposive sampling. The data were analyzed using descriptive statistics, regression analysis, and Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that while user type has no significant influence on fintech usage patterns, the frequency and transaction volume differ significantly across fintech application types before and after COVID-19. Moreover,

perceived risk demonstrates a significant impact on user type, whereas perceived benefit does not. The study concludes that behavioral factors, rather than demographic or categorical ones, drive fintech adoption decisions. These insights provide a foundation for policymakers and fintech service providers to enhance trust, reduce risk perceptions, and promote inclusive digital financial ecosystems in Sri Lanka.

Keywords: Fintech Adoption, User Behavior, Perceived Risk and Benefit, Accounting Professionals, COVID-19 Impact

INTRODUCTION

The world is moving into a completely digital age with the expansion of the internet-based economy. The decrease in the hesitancy among different users, i.e., young and elderly users, to adopt online channels, not only for the usage of financial information search but also for the usage of financial transactions, has enabled and driven the evolution of the Financial Technology (Fintech) era (Gomber et al., 2017)[1]. The COVID-19 pandemic has also pushed the Fintech industry towards unexpected growth. It was identified that E-Commerce and Mobile Wallet payments have increased by 35.5% between January and June 2020 in the retail sector (Sebastiani & Kazi, 2020).

[1] Fintech refers to the applications of computer, mobile, and other related digital technologies in financial services and is significantly redefining the working structure and the models of the financial industry and entities (Sangwan et al., 2020).

The number of studies covering both the benefits and the risks in Fintech is limited, as different user groups have perceived the benefits and risks differently to adapt to new payment technologies. Also, there is a need to analyze the factors continuously affecting the usage of Fintech (Kim et al., 2010; Zhou, 2013). Most of the studies have looked at fixed Fintech applications; however, newer, improved applications are not explored, such as Bitcoin, Ethereum, internet insurance, personal financing, equity, financing and retain investment Fintech tools and software (Ryu, 2018). In similar studies conducted on Fintech to understand the acceptance of technology, the Technology Acceptance Model (TAM) has been used (Davis, 1989). It considers two primary factors: i) perceived ease of use and ii) perceived usefulness, to consider the factors influencing an individual's intention to use new technology (Charness & Boot, 2015). The expansion of the business scope of Fintech organizations in the financial sector beyond online platforms and into mobile platforms through mobile payments and mobile remittance has challenged the traditional banking and financial organizations to be innovative and adopt divergent thinking to differentiate the services offered compared to other companies (Iman, 2018; Ryu, 2018).

The struggle of the firms to be innovative and differentiative has made it difficult for these organizations to increase the user base, leading them to try various methods to convert existing customers to adopt internet banking (Johan, 2020). The amount of studies on the topic of Fintech is also limited and it is necessary to identify the factors that help determine why people continue to use Fintech, as the previous studies only focus on the main drivers influencing user behavioral intention in the literature (Cheng et al., 2006; Kim et al., 2010; Liang & Yeh, 2011; Ryu, 2018; Zhou, 2013).

Further, despite the rapid growth of Fintech adoption in emerging economies, the research problem concerning how user characteristics and behavioral factors influence Fintech usage remains insufficiently explored. Previous studies have primarily focused on general consumers or banking clients, often overlooking financially literate professionals whose decisions are influenced by both expertise and behavioral tendencies (Kim, Mirusmonov, & Lee, 2010; Ryu, 2018; Das & Das, 2020). This gap limits understanding of how cognitive and psychological factors, such as perceived risk and perceived benefit, shape Fintech adoption in contexts characterized by varying levels of financial literacy and technological exposure.

Accordingly, the objectives of this study are (1) to determine the frequency, volume, and application usage based on the different user types and their impact (2) to determine different applications used according to frequency, volume and application usage and their impact (3) to identify the perceived risk and benefits of Fintech based on different user types and their impact.

LITERATURE REVIEW

This study focuses on two theories, as Behavioral Finance[2] theory and the E-commerce theory. When identifying the perceived benefit according to Ryu (2018), "A perceived benefit is defined as a user's perception of the potential that Fintech use will result in a positive outcome". Other similar studies have discussed the same ideology and have stated that there is a positive correlation between the perceived benefit of the user influencing the decision to use IT services for various applications. (Abramova & Bohme, 2016; Benlian & Hess, 2011; Farivar & Yuan, 2014; Jung et al., 2009; Lee et al., 2013). Another study conducted on mobile payments revealed that the usage

[2] Behavioral Finance is a field of research that focuses on how psychological influences affect market outcomes. In General, behavioral finance analyzes different results in different sectors and industries to understand the sector better. The key factor influencing the Behavioral finance is the psychological biases of individuals (Hayes, 2021).

of mobile payment devices is impacted drastically by the user's perception (Yan et al., 2012).

With the adoption of Fintech, users have perceived benefits and risks that individually vary for the adoption of Fintech (Ryu, 2018). According to Lee, Park and Kim (2013), a study was conducted to examine the benefits and risk factors that influence the intention of the user to disclose information on social network services and as a result, determined that users' behavior would expand their benefits and reduce their risks. Another study conducted on social commerce adoption has recommended a theoretical model to analyse and understand users' social network adoption behaviour, considering the perceived benefits, perceived risks, and trust from the benefit–risk framework. In that study, Farivar and Yuan (2014) adopted two positive factors as perceived benefits, i.e., social and commerce benefits, and two negative factors as perceived risks i.e., social and commerce risks.

Theoretical Foundation and Justification

The conceptual framework of this study was developed by integrating both theoretical perspectives and empirical evidence, drawing primarily on Behavioral Finance Theory and E-Commerce Theory to explain the determinants of Fintech adoption among different user types.

Behavioral Finance Theory explains how individuals' financial decisions are influenced by cognitive biases, perceived risks, and subjective evaluations of benefits (Ryu, 2018). In this study, the constructs of perceived risk and perceived benefit are directly derived from this theoretical foundation. These variables capture the psychological tendencies of users—such as overconfidence, loss aversion, and trust sensitivity—that shape Fintech usage decisions. By associating these behavioral aspects with user type (early or late adopters), the theory helps explain heterogeneity in Fintech adoption behavior beyond purely rational considerations.

E-Commerce Theory, on the other hand, views technology-based financial transactions as exchange processes shaped by trust, convenience, perceived value, and system reliability (Lee & Teo, 2015). This perspective aligns with the study's examination of frequency, transaction volume, and application usage as behavioral indicators of user engagement with fintech platforms. The integration of this theory allows the study to extend beyond individual psychological factors and capture the structural and experiential dimensions of online financial behavior.

Although the Technology Acceptance Model (TAM) has been extensively applied in Fintech research (Davis, 1989; Zhou, 2013), it focuses mainly on perceived usefulness and ease of use. These dimensions, while valuable for explaining initial technology adoption, provide limited insight into users' behavioral continuance, risk attitudes, and post-adoption experiences—particularly relevant in financial decision-making contexts characterized by uncertainty. Given that Fintech adoption inherently involves financial risk, regulatory exposure, and trust considerations, Behavioral Finance Theory and E-Commerce Theory offer a more comprehensive and contextually appropriate framework for understanding the complex interplay of psychological, behavioral, and technological factors influencing Fintech usage in Sri Lanka.

Financial Technology is not a stand-alone segment in many cases; it is an incorporated backbone service provider in industries and domains such as banking and finance, insurance, retail (consisting of both the traditional and the online platforms), healthcare, telecommunication, etc. These domains have been explored by many successful ventures, both locally and at a global level. Researchers have argued that Fintech is shaping the future of financial industries (Lee & Teo, 2015). Magnuson (2018) claims that all aspects are changed from the fundamentals through financial technologies, from the way that banking works, to the way that capital is raised, even to the very form of money itself. Accordingly, the Fintech landscape can be broken down into 4 sections: (1) credit deposits and capital raising services, (2) payments, clearings, and settlements services, (3) investment management services, and (4) insurance (Dharmadasa, 2021, as cited in Pilkington, 2016).

The growth in Sri Lanka for Fintech applications is still at an early stage, with e-wallet applications such as Epic Mobile wallet by Epic Technology Group, Frimi by Nations Trust Bank, Pay by Genie by Dialog, and Upay by Sanasa Development Bank PLC being some players to be mentioned in the Local markets. Mobile Payment applications have taken the rise in Sri Lanka and according to the Central Bank of Sri Lanka (2020), there are two types of Licensed Service Providers of Mobile Payment Systems: Operators of Customer Account-based Mobile Payment Systems and Operators of Mobile Phone-based e-money Systems.

When considering the Sri Lankan Context, the provision of access for customers to the service through their mobile phones from a licensed service provider is known as Customer Account-based Mobile Payment Systems (Mobile Phone Banking). According to the Central

Bank Payment Bulletin (2020), for the 1st quarter ended 2021, the number of licensed service providers is 12, having a total value transacted of Rs 115.4 billion, which is a 22.1% increase compared to the transaction value of the 3rd quarter of 2019.

When breaking down the Account-based Mobile Payment Systems, it was identified that for the 4 quarters in 2020, the total transaction volume of the period was 24.6 million transactions, generating a total value of 455.9 billion Sri Lankan Rupees. There has been a fluctuation in the transaction progression during this period, where there has been a drop of 35% in the volume and a 27% drop in the total value of the transactions in the 2nd quarter, when compared with the 1st quarter of 2019. The decrease was calculated at 11%. Accordingly, in the 3rd quarter, there has been a growth of 85% in terms of volume of transactions and an increase of 37% in transaction value. When the transaction volume is compared with the previous year's numbers, it can be identified that the highest growth compared to the previous quarter was recorded in the 1st quarter of 2020 at 78%. When identifying the Overall growth of the Customer Account-based Mobile Payment Systems as mentioned above the growth for 2020 (for 3 quarters) is 14% compared to 2019 it seems to show a quantum leap in the applications being utilized compared to 2018 in terms of volume and value where the total volume increased by 140% from 2018 and the value of transaction grew from Sri Lankan rupees 120 million to Sri Lankan rupees 274.96 billion in 2019. The leap happened after the 2nd quarter of the year.

When considering the Mobile Phone-based e-money Systems in Sri Lanka, there are 2 players in the market, namely eZcash and mCash. The Central Bank has classified the usage of the Sri Lankan customer base in the following categories: utility bill payment, money transfer, institutional payments, purchase / over-the-counter transactions, internet transactions, and other transactions. Initially, when looking into the sectors, the fluctuations are relatively below 5 % for all 3 years. The largest volume of transactions takes place for utility bill payments, with an average of around 88% of the total transaction volume from 2018 to 2020, which is only 64% of the total value of transactions for the same 3-year period. This payment has the highest share in terms of the total transaction value. If the transactions with higher values are considered, it would be Institutional payments, as these types of transactions averaged 5% in terms of total transaction volume in 2020, but were 23% of the total transaction value of the entire Mobile Phone-based e-money System. Money Transfers were around 6.8% of the total transaction value, but it was 3.5% of the total volume of the transactions (Central Bank Payment Bulletin - Quarterly, 2017: 2021).

The framework diagram pictured below has been developed conceptually based on what was identified under the research objective and the literature review, which identifies the different user types to determine the volume, usage, and frequency. This framework also breaks down how volume, usage, and frequency are significant to applications considered for the study and it also checks the impact of the perceived risk & benefit for the different user types.

Conceptual Framework

The conceptual framework of this study has been developed based on the theoretical underpinnings of Behavioral Finance Theory and E-Commerce Theory, as well as empirical findings from prior Fintech research. The framework illustrates the relationships between user type (early and late adopters) as the key categorical variable and several Fintech usage behavior dimensions, namely frequency of usage, transaction volume, and application usage, which serve as the principal dependent variables. In addition, perceived risk and perceived benefit are incorporated as behavioral constructs that influence user type and, consequently, Fintech adoption decisions (Ryu, 2018; Pavlou, 2003;

Lee & Teo, 2015). The model proposes that while behavioral perceptions shape users' adoption tendencies, these tendencies, in turn, determine the extent and nature of Fintech usage across different application types and time periods (before and after COVID-19). Thus, the conceptual framework integrates psychological and behavioral factors to explain the heterogeneity in Fintech adoption behavior among accounting professionals in Sri Lanka. Based on the above discussion conceptual framework for the study is developed as follows:

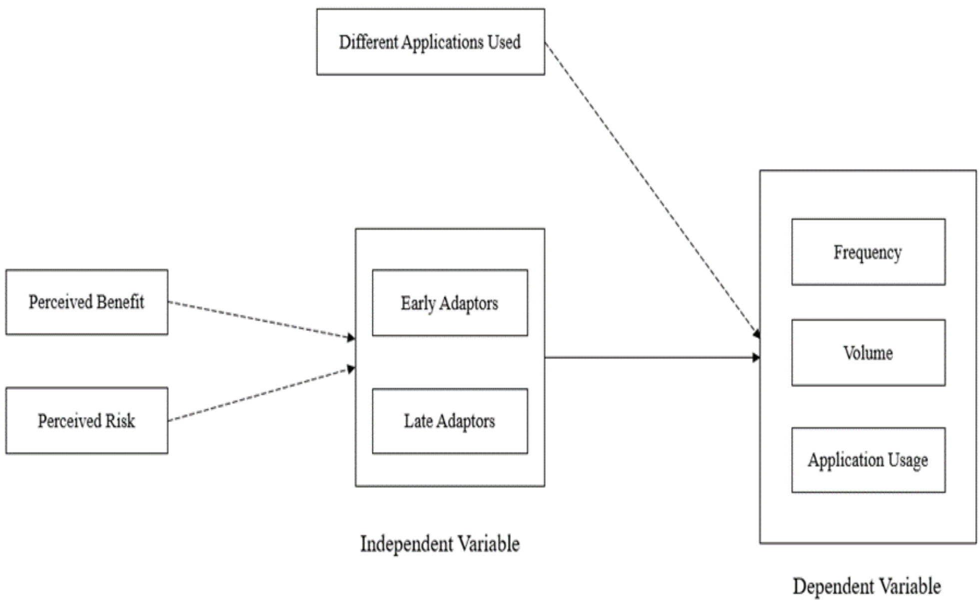

Figure 1: Conceptual Framework

Hypotheses Development

Based on the user types and their impact from the above, the following hypothesis was developed to be tested:

H1: There is a significant impact of frequency, volume, and application usage on user type.

H2: There is a significant impact of different fintech applications on the frequency before COVID-19.

H3: There is a significant impact of different fintech applications used on the frequency before COVID-19.

H4: There is a significant impact of different fintech applications used on volume before COVID-19.

H5: There is a significant impact of different fintech applications used on volume after COVID-19.

H6: There is a significant impact of different fintech applications used on application usage before COVID-19.

H7: There is a significant impact of different fintech applications used on application usage after COVID-19.

H8: There is a significant impact of perceived benefit on the category of user.

H9: There is a significant impact of perceived risk on the category of user.

METHODOLOGY

The data for this study were collected through a survey (questionnaires) from accounting professionals living in the Western Province, Sri Lanka. Sri Lanka's fintech ecosystem remains at an emerging stage of maturity, with limited empirical evidence on user behavior and adoption dynamics. While international studies often confirm that Fintech usage increases with user familiarity and digital access, such assumptions may not hold uniformly in developing economies where infrastructural, regulatory, and trust-related barriers persist. This study, therefore, addresses a distinct contextual gap by examining how fintech usage patterns differ across application types and user categories within Sri Lanka's evolving digital finance landscape.

The mode of collection, due to the pandemic situation, was via an online platform using the tool Google Forms. Accounting professionals were purposefully selected as the study's sample because they represent an informed and financially literate user group positioned between individual consumers and institutional actors. Their behavioral responses provide valuable insights into adoption facilitators and constraints that shape Fintech diffusion in a low-penetration market (Das & Das, 2020). The data collected from the responses of the participants of the survey were analysed to better understand the impacts.

Accordingly, hypotheses H2 to H6 are not intended to merely replicate existing global findings but to test whether impacts—such as the link between application type, frequency, and volume of use—are consistent in a context characterized by uneven technological readiness and pandemic-induced behavioral acceleration. This contextual focus enables the study to contribute new empirical evidence on Fintech adoption under external shocks and infrastructural limitations, offering implications for both local policymakers and regional Fintech strategists.

The data collected from the questionnaire distributed were analysed using SPSS statistical software and Smart PLS for Structural Equation Modelling. The first objective of the study is to determine the frequency, volume, and application usage based on the different user types and their impacts. To analyse the first objective, descriptive statistics were used to determine the frequency, volume, and application usage based on the different user types and to explore the impact of frequency, volume, and application usage on the different user types, correlation, and regression analysis were used. The regression model can be specified as follows:

Late Adopter = $\beta_1 + \beta_2$ Application Usage + β_3 Volume + β_4 Frequency + ε_i

Early Adopter = $\beta_1 + \beta_2$ Application Usage + β_3 Volume + β_4 Frequency + ε_i

The second objective of the study is to determine different applications used according to frequency, volume and application usage and their impacts. Similar to the first objective, descriptive statistics were used to determine different applications used according to volume value and frequency, while the regression analysis was used to analyze the relationship and impacts of different applications used on volume and frequency.

The regression model can be specified as follows:

Frequency After = $\beta_1 + \beta_2$ Electronic or Online or Payment Application + β_3 Trading or Investment Application + β_4 Loan Applications + β_5 Fund Management Application + β_6 Personal Insurance Applications + ε_i

Frequency Before = $\beta_1 + \beta_2$ Electronic or Online or Payment Application + β_3 Trading or Investment Application + β_4 Loan Applications + β_5 Fund Management Application + β_6 Personal Insurance Applications + ε_i

Volume After = $\beta_1 + \beta_2$ Electronic or Online or Payment Application + β_3 Trading or Investment Application + β_4 Loan Applications + β_5 Fund Management Application + β_6 Personal Insurance Applications + ε_i

Volume Before = $\beta_1 + \beta_2$ Electronic or Online or Payment Application + β_3 Trading or Investment Application + β_4 Loan Applications + β_5 Fund Management Application + β_6 Personal Insurance Applications + ε_i

Application Usage After = $\beta_1 + \beta_2$ Electronic or Online or Payment Application + β_3 Trading or Investment Application + β_4 Loan Applications + β_5 Fund Management Application + β_6 Personal Insurance Applications + ε_i

Application Usage Before = $\beta_1 + \beta_2$ Electronic or Online or Payment Application + β_3 Trading or Investment Application + β_4 Loan Applications + β_5 Fund Management Application + β_6 Personal Insurance Applications + ε_i

The third objective of the study is to identify the perceived risk and benefit of fintech based on different user types and their impacts. Structural equation modelling was used. This analyzes the coefficients of the paths and the validity and reliability of the variables for the model. It also examines the model fit.

User Type	Early Adopter	Late Adopter
Frequency		
Before COVID-19	4 times a month	Below 4 times a month
After COVID-19	8 times a month	4 times a month
Volume		
Before COVID-19	Between Rs. 10,001 to 50,000	Between Rs. 10,001 to 50,000
After COVID-19	Between Rs. 10,001 to 50,000	Between Rs. 10,001 to 50,000
Application Usage		
Before COVID-19	I am completely dependent on these applications for my transactions	For a combination of 2 – 4 more services
After COVID-19	For a combination of 2 – 4 more services	For a combination of 2 – 4 more services

Table 1: User Analysis (Frequency, Value and Application Usage)

Source: Author Complied

RESULTS

From the 93 participants, it was identified that only 56 participants have been using Fintech applications other than mobile / internet banking applications and e-passbook. It was also recognized that from the 56 participants, 46 were early adopters, while 10 were late adopters.

To determine the user type, a question targeting the participants' technological attitude was tested, and based on the response provided, the users were classified as early adopters and late adopters. On average, it has been identified that the average usage volume for early adopters has increased after COVID-19, from being 4 times a month to 8 times a month. Conversely, when considering the late adopters, their usage has also improved from being used below 4 times a month before COVID-19 to 4 times a month after COVID-19.

In the meantime, when looking into the value of using, it has been stagnant for both early adopters and late adopters despite the COVID-19 situation and it has averaged at a value between Rs. 10,001 to Rs. 50,000. Interestingly, when looking at the mean of the different applications used, early adopters were completely dependent on financial technological applications before COVID-19, but after the COVID-19 situation, the average has shifted to a combination of 2 – 4 services. Whereas when considering the late adopters there has been no change in the volume of applications used despite the COVID-19 situation and the usage has been averaged at a combination of 2 – 4 service applications, in addition, it was also identified that from the respondents who were above the age of 55, 70% of the adopters are categorized as early adopters and 33.3% are late adopters who are members/affiliates of an accounting professional body.

Results as per the objectives

Objective 01: To determine the frequency, volume, and application usage based on the different user types and their impacts

I. To determine frequency based on the different user types

Based on the analysis conducted out of the 72 early adopters, 46 are using a COVID-19 application other than mobile / internet banking application / e-passbook, it could be understood that 4.3% of respondents who are early adopters did not use these applications considered for this study, before the COVID-19 pandemic the majority of the early adopters at 60.9% were using these applications below 4 times a month but after the COVID-19 situations, 60.7% early adopters under this category has shifted to use these applications 4 time or more than 4 times a month. 19.6% of the users do not see a change in the usage pattern despite the situation. It can also be identified that users who use these applications more than 8 times a month have grown by 850% compared to the time before COVID-19, and these respondents account for 37%. Those who use the applications 4 times a month have increased by 366% compared to the situation before COVID-19. Early adopters who use the application below 4 times a month and 4 times a month account for 23.9% in each of the sub-sectors. Early adopters using the application 8 times a month also increased by 350% which accounts for 15.2% of the respondents who are early adopters.

70% of late adopters were reluctant to be dependent on Fintech applications before COVID-19 as their usage indicates that they have not used these applications less than 4 times a month, but the pandemic has changed the perception of 28.5%. Users who have adopted these Fintech options more than 8 times a month have grown by 100%. It was also identified that there was 01 respondent who had adopted using a Fintech application after COVID-19, but no late adopter seems to have the same frequency of usage before and after COVID-19. When considering the value spent on these different applications by the early adopters and late adopters, the results were identified as follows. A significant improvement has occurred where these applications are used 4 times a month and more than 8 times a month, also respondents who have not been using Fintech applications before COVID-19 have shifted to using these applications more. Also, it was identified that some users have no change in their usage patterns.

II. To determine volume based on the different user types

Early adopters who have been using below Rs. 10,000 a month have decreased by 42.9% after the COVID-19 situation, while the spending between Rs. 10,001 to Rs. 50,000 has increased by 83.3%. Early Adopters are those who have been spending over Rs. 100,001 before COVID-19, have not shifted their usage patterns and they have been spending the same. The early adopters who have spent between Rs. 50,001 to Rs. 100,000 have increased by 66.7%.

It was identified that late adopters who had been using Fintech before COVID-19 have started to spend more after the COVID-19 situation, as respondents who have been spending below Rs. 10,000 has reduced by 71.4% while the spending between Rs.10,001 to Rs.50,000 has increased by 150%, those who have started to spend between Rs.50,001 to Rs.100,000 has increased by 200%. Like Early adopters, late adopters who have been spending over Rs. 100,000 also have not changed and have been held constant before and after the pandemic.

When looking at the overall volume usage by both early and late adopters, it can be identified that spending between Rs. 10,001 to Rs. 50,000 has seen a significant improvement in both early and late adopters before and after COVID-19. Another pattern was also identified where respondents' early adopters and late adopters spending over Rs. 100,001 have been stagnant before and after COVID-19.

III. To determine usage based on the different user types

From the situational analysis, before COVID-19, it can be seen that there have been users who have not been using Fintech applications. Users who have been using a combination of 2 – 4 services mentioned above have increased by 325% after the COVID-19 pandemic and the number of users who have become dependent on these types of Fintech applications has also increased by 100%. Another observation arising from the above 2 figures is that the number of respondents who stated that they use Fintech applications only when they have no other option has also reduced by 25% after COVID-19. A slight drop of 13.0% has been incurred in the early adopters who have been using these applications for one purpose

The observations arising from the late adopters seem to have changed before and after the COVID-19 situation. The number of users who have been using these applications for only one purpose has decreased by 66.6% after the COVID-19 situation and late adopters who were not using any Fintech application before the COVID-19-19 pandemic have also adopted Fintech applications after this situation. On the other hand, it can be identified that the number of late adopters who use a combination of 2 – 4 or more services has increased by 166.6%. which indicates that the late adopters have become more user-friendly and comfortable with the applications.

When analyzing the impacts, it was identified that the user type and the volume, application usage, and frequency are not interrelated and do not have significance to the early adopters or late adopters. (Das & Das, 2020; Gulamhuseinwala et al., 2015).

Objective 2: To determine different applications used according to frequency, volume, and application usage and their impacts.

This is to identify the different applications used by the respondents other than mobile / internet banking and e-passbook. The applications in focus include Trading applications (e.g., TWS, CSE Applications, or other similar share trading applications, crypto-wallets), Mobile Lending Applications (e.g., Cash wagon), Mobile wallets (e.g., Genie, eZ Cash, FriMi, mCash, DFCC – Virtual wallet, Upay, Solo, PayPal), Insurtech Apps (e.g., SLIC, Insureme, Clickme), Personal Finance Management Apps (E.g., Mint, Check, You need a Budget). Table 2: Summary of Users based on the different applications used identifies and summarizes the different applications used by early and late adopters.

Application	Early Adopter (%)	Late Adopter (%)
Trading Application		
Yes	37.0%	40.0%
No	63.0%	60.0%
Mobile Lending Application		
Yes	10.9%	10.0%
No	89.1%	90.0%
Mobile Wallet		
Yes	76.1%	70.0%
No	23.9%	30.0%
Insure Tech		
Yes	10.9%	10.0%
No	89.1%	90.0%
Personal Finance Management		
Yes	26.1%	50.0%
No	73.9%	50.0%

Table 2: Summary of the User based on the different applications used

Source: Author Complied

Table 2 indicates the breakdown of the different applications based on users and it can be identified that Trading applications are used by 21 respondents, which is the second most used type of application by both early and late adopters. With an average usage of 73.1%, Mobile wallets are a significantly used application by both early and late adopters. Mobile lending applications and Insure Tech applications have been the least used applications by the respondents, where, on average, 10.5% of the respondents out of the 56 users are using these applications.

Out of the respondents who are early adopters and are using Fintech applications, the motive of these users for these application usages can be identified that 87.0% of the early adopters are using these applications for payments and online transactions, while 37.0% of the early adopters use these applications for trading or investment purposes. 14 respondents out of the 46 respondents who are early adopters have mentioned that their purpose for using of Fintech application is fund management. 08.7% and 02.2% of the respondents have stated that personal finance applications and obtaining loans are the purposes of using Fintech applications, respectively.

Conversely, late adopters also seem to reveal an interesting pattern where 90% who are using Fintech applications seem to have the motive of payments and online transactions. 40% are using Fintech applications for trading and investment, while 30% are using Fintech for fund management, and no late adopter uses Fintech for obtaining loans.

Dependent variable	R Square	Adjusted R Square	Sig
Frequency Before	0.236	0.159	0.017^b
Frequency After	0.312	0.243	0.002^b
Volume Before	0.219	0.141	0.026^b
Volume After	0.276	0.204	0.005^b
Application Usage Before	0.172	0.089	0.084^b
Application Usage After	0.143	0.057	0.159^b

Table 3: Model Summary (Frequency, Volume and Application Usage)

Source: Author Complied

Further, when analysing the second objective of the study, it was identified that the R-squared for the 23.6% variance on the dependent variable (Frequency before) is explained by the independent variable (Applications used). In the meantime, the significance of frequency before was 0.017, indicating that Frequency before is significantly related to the Fintech application used. Based on the results, there is sufficient evidence to prove that there is a significant impact of different Fintech applications used before COVID-19 on frequency. Therefore, the null hypothesis is rejected (with reference to the alternative hypothesis H2).

When considering the R-squared for frequency after, it was identified that 31.2% of the variance on the dependent variable (Frequency after) is explained by the independent variables (Applications used). The significance of the frequency after was 0.002, indicating that frequency after is significantly related to the Fintech application used. Based on the results, there is sufficient evidence to prove that there is a significant impact of different fintech applications on frequency on after COVID-19. Therefore, the null hypothesis is rejected (with reference to the alternative hypothesis H3).

From the above summary table, the variable volume before the R-squared was interpreted as 21.9% variance on the dependent variable (volume before) is explained by the independent variable (Applications used). The significance for the volume before was 0.026, indicating that the volume before is significantly related to the Fintech application used. Based on the results, there is sufficient evidence to prove that there is a significant impact of different Fintech applications used on volume before COVID-19. Therefore, the null hypothesis is rejected (with reference to the alternative hypothesis H4).

When considering the R-squared for volume after, it was identified that 27.6% of the variance on the dependent variable (volume after) is explained by the independent variables (Applications used). The significance for the volume after was 0.005, indicating that volume after is significantly related to the application used. Based on the results, there is sufficient evidence to prove that there is a significant impact of different Fintech applications used on volume after COVID-

19. Therefore, the null hypothesis is rejected (with reference to the alternative hypothesis H5).

Finally, when considering the application usage, the R-squared for application usage before, it was identified that 17.2% variance on the dependent variable (usage before) is explained by the independent variable (Applications used). The significance for the application usage before was 0.084, indicating that there is an absence of evidence to indicate a significance between application usage before and the Fintech application used before COVID-19. Therefore, the null hypothesis is accepted (with reference to the alternative hypothesis H6).

When considering the R-squared for application usage after, it was identified that 14.3% of the variance on the dependent variable (usage after) is explained by the independent variables (Applications used). The significance for the application usage after was 0.159 and there is an absence of evidence to indicate a significance between application usage after and Fintech application use after COVID-19. Therefore, the null hypothesis is accepted (with reference to the alternative hypothesis H7).

Furthermore, when breaking down the coefficients of the frequency, volume, and application usage against the electronic/online / payment application, trading or investment application, loan applications, fund management, and personal insurance applications, it can be identified as follows.

Frequency	B	t	Sig.
Frequency After			
(Constant)	2.941	6.284	0.000
Electronic / Online / Payment Application	-0.916	-2.045	0.046
Trading or Investment Application	1.116	3.816	0.000
Loan Applications	0.679	0.563	0.576
Fund Management Application	0.013	0.038	0.970
Personal Insurance Applications	0.166	0.303	0.763
Frequency Before			
(Constant)	3.042	4.568	0.000
Electronic/online / payment application	-1.532	-2.404	0.020
Trading or Investment application	0.644	1.548	0.128
Loan Applications	-1.427	-0.831	0.410
Fund Management Application	-0.646	-1.360	0.180
Personal Insurance Applications	1.918	2.457	0.018

Table 4: Coefficients of Fintech applications (Frequency)

Source: Author Complied

From above table 4 it can be identified that when considering the Frequency of usage of Fintech applications after COVID-19, Electronic / online / payment application, Trading or Investment applications have been used significantly compared to the other applications and have a significant impact on the frequency of usage after COVID-19 whereas when looking at the scenario before COVID-

19 it can be identified that Electronic / online / payment application and personal insurance applications have been significant in the usage with a value less than 0.05.

Volume	B	t	Sig.
Volume After			
(Constant)	1.530	4.392	0.000
Electronic / Online / Payment Application	0.040	0.120	0.905
Trading or Investment Application	0.558	2.562	0.013
Loan Applications	0.897	0.999	0.323
Fund Management Application	0.324	1.303	0.199
Personal Insurance Applications	0.651	1.595	0.117
Volume Before			
(Constant)	1.220	3.258	0.002
Electronic/online / payment application	-0.031	-0.085	0.932
Trading or Investment application	0.484	2.067	0.044
Loan Applications	0.106	0.110	0.913
Fund Management Application	0.402	1.507	0.138
Personal Insurance Applications	0.819	1.866	0.068

Table 5: Coefficients of Fintech applications (Volume)

Source: Author Complied

From the above table, it can be identified that when considering the volume of usage of Fintech applications after COVID-19, Trading or Investment applications have been used significantly compared to the other applications and have a significant impact on the volume of usage after COVID-19. When looking at the scenario before COVID-19, it can be identified that it has been a similar situation as volume after COVID-19; therefore, the significance in the volume after and before is at a value less than 0.05.

Usage	B	t	Sig.
Usage After			
(Constant)	2.037	5.555	0.000
Electronic / Online / Payment Application	-0.152	-0.432	0.667
Trading or Investment Application	-0.117	-0.509	0.613
Loan Applications	-0.310	-0.328	0.744
Fund Management Application	-0.381	-1.459	0.151
Personal Insurance Applications	0.923	2.148	0.037
Usage Before			
(Constant)	2.133	2.713	0.009
Electronic/online / payment application	-0.151	-0.201	0.841
Trading or Investment application	0.033	0.067	0.947
Loan Applications	1.839	0.907	0.369
Fund Management Application	1.395	2.488	0.016
Personal Insurance Applications	-0.247	-0.269	0.789

Table 6: Coefficients of Fintech applications (Usage)

Source: Author Complied

The results indicate that trading and investment applications exert a stronger and more consistent influence on both usage frequency and transaction volume before and after the COVID-19 pandemic. This finding is theoretically supported by Behavioral Finance Theory, which posits that financially literate users perceive higher utility and control when engaging in investment-related Fintech tools, as these applications align with risk–return motivations and self-directed financial behavior (Ryu, 2018; Li et al., 2020). Users in this category often display heightened confidence and engagement in response to real-time market information—characteristics that were amplified during the pandemic when digital investment activity surged due to mobility restrictions and market volatility.

From an E-Commerce Theory perspective, these applications also deliver stronger perceived value through interactive interfaces and immediate transactional feedback, which reinforce both functional and experiential satisfaction (Lee & Teo, 2015). In contrast, mobile wallet and insurance applications, though widely adopted, exhibit lower cognitive involvement because their use tends to be habitual or necessity-driven rather than investment-motivated. This distinction explains their weaker statistical significance: such applications serve routine financial functions with limited perceived differentiation (Gomber et al., 2017; Zhou, 2013).

Thus, rather than reflecting mere frequency effects, the stronger relationships observed for trading and investment Fintech illustrate how perceived risk–reward balance and information empowerment influence user engagement. These findings reinforce the argument that behavioral and experiential factors—more than technological convenience alone—shape Fintech adoption patterns in emerging markets like Sri Lanka.

When considering the Frequency of usage of Fintech applications after COVID-19, Electronic / online / payment applications, Trading or Investment applications have been used significantly compared to the other applications and have a significant impact on the frequency of usage after COVID-19. Whereas when looking at the scenario before COVID-19, Electronic/online payment applications and personal insurance applications were significant. High penetration of smartphones and other connected devices has enabled the adoption of digital solutions and the frequency of these applications has increased (Merrey, 2017).

Objective 3: To identify the perceived risk and benefit of Fintech based on different user types and their impacts.

The third objective of the study is to understand if there is any significant impact between the perceived risk and perceived benefit and the user as an early adopter or a late adopter.

Perceived Benefit/Risk	Factor Loading	AVE	Cronbach's Alpha
Perceived Benefit		0.609	0.881
Innovation	0.736		
Economic Benefit	0.692		
Convenience	0.829		
Seamlessness	0.861		
Approval & Security	0.764		
Unavailability of other options	0.787		
Perceived Risk		0.660	0.895
Personal Data	0.819		
Personal Risk	0.869		
Legal Risk	0.827		
Financial Risk	0.896		
Negative Impact and Experience	0.768		
Lack of knowledge	0.678		

Table 7: Validity and Reliability of Users (Early Adopter & Late Adopter)

Source: Author Complied

From the above Table 7 Construct Validity and Reliability of Users, it can be identified and interpreted that the factor loading for each variable should be higher than 0.5, but in the above analysis, variables under perceived benefit, such as Brand Image, has a factor loading of 0.317 and the variable of Recommendation has a factor loading of 0.308. Similarly, on the perceived risk variable it can be identified that the Fear of technology has a factor loading of 0.436, in addition to the factor loading the Average Variance Extracted (AVE) should also be greater than 0.5 but the AVE of the perceived benefit variable is 0.422 after the removing the variable with the factor loading below 0.5, the Construct Validity and Reliability of Users can be shown as follows.

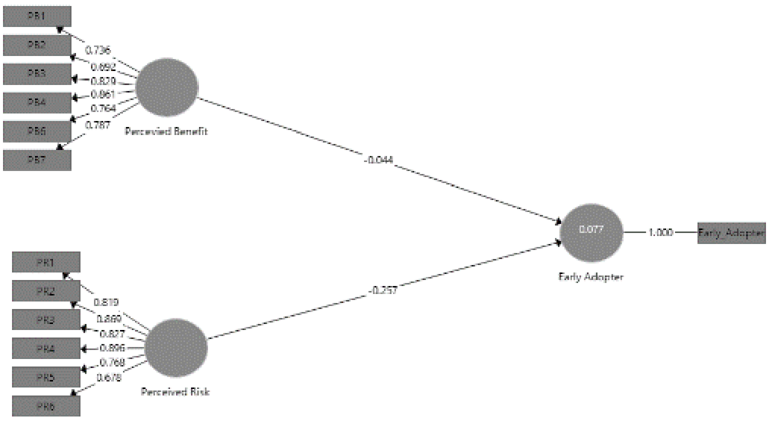

Figure 2: Perceived Benefit and Risk between Late Adopters

Source: **Author Complied**

The structural equation models show the paths hypothesized in a structural framework and are assessed based on R^2 and Q^2. To determine the goodness of each structural path of the model, R^2 is used for each dependent variable (Briones Peñalver et al., 2018). As the values of the R^2 factors are less than 0.1, it was identified that predictive capabilities for this model cannot be established. In addition to the above, when testing the model fit, the SRMR value should be below 0.10 (Sarstedt & Christian M. Ringle, 2017), but this model has a value of 0.080, indicating the model is fit.

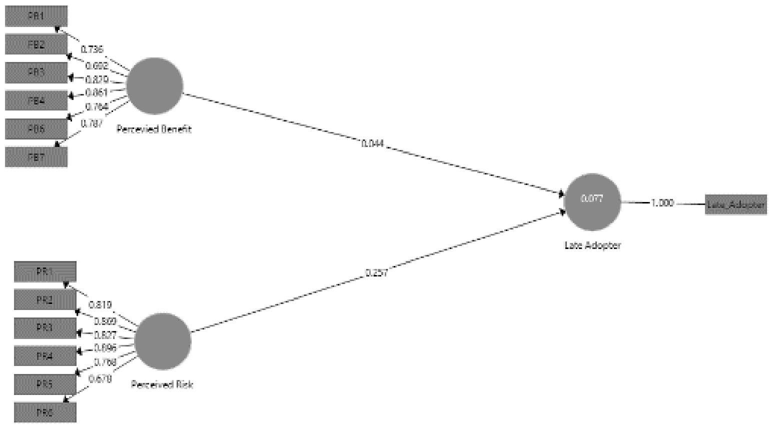

Figure 3: Perceived Benefit and Risk between Late Adopters

Source: Author Complied

Perceived benefit for user category does not have a significance value for early adopters ($\beta = -0.044$, $t = 0.336$, $p = 0.715$) and late adopters ($\beta = 0.044$, $t = 0.360$, $p = 0.719$), and the R square value also explains that only 7.7% of the variance in the dependent variable (early adopter or late adopter) is explained by the independent variable (perceived benefit). Based on the results, there is an absence of evidence to indicate that there is sufficient evidence of a significant impact of perceived benefit on the category of user (early adopter or late adopter), therefore, the null hypothesis is accepted (with reference to the alternative hypothesis H8).

On the other hand, when considering perceived risk and the user category, there is a significant impact of perceived risk on early adopters ($\beta = -0.257$, $t = 2.736$, $p = 0.006$) and late adopters $\beta = 0.257$, $t = 2.744$, $p = 0.006$). The R-squared value also explains that only 7.7% of the variance in the dependent variable (early adopter or late adopter) is explained by the independent variable (perceived risk). Based on the results, there is sufficient evidence to prove there is a significant impact of perceived risk on the category of user (early adopter or late adopter); therefore, the null hypothesis is rejected (with reference to the alternative hypothesis H9).

In conclusion, when considering the perceived risk, there is an impact on both early adopters and late adopters when deciding the Fintech usage (Li et al., 2020; Liébana-Cabanillas et al., 2014; Pavlou, 2003; Saleem, 2021). When considering the perceived benefit to both early and late adopters, there is no significant impact of perceived benefit on the category of users.

CONCLUSION

It was identified that early adopters have changed their frequency of usage to 8 times a month after COVID-19 from 4 times a month before COVID-19, whereas late adopters have changed their usage pattern from using less than 4 times a month before COVID-19 to 4 times a month after COVID-19. When considering the volume of usage, both early adopters and late adopters before and after COVID-19 have not changed the value of spending, as the amount has been between Rs. 10,001 to Rs. 50,000. When considering the application usage, it can be identified that early adopters were completely dependent on these applications for their transactions before COVID-19, but this has changed after COVID-19, where a combination of 2 - 4 applications has been used. On the other hand, no change in the pattern was found for late adopters, as they have been using a combination of 2 - 4 applications before and after COVID-19. Additionally, it was identified that there is no significant impact between these variables and the user type.

According to the second objective, it was identified that there is a significant impact of frequency on volume before and after COVID-19 and the different applications used. However, sufficient evidence was not available to prove that there is a significant difference between application usage and the applications used before and after COVID-19.

Considering the third objective, it was identified that perceived risk had a significant impact on early and late adopters, whereas for perceived benefit, sufficient evidence was not available to prove a significant impact on late or early adopters.

The findings demonstrate that perceived risk exerts a significant influence on both early and late adopters, highlighting that Fintech adoption is not merely a technological decision but a behavioral and psychological one. Consistent with Behavioral Finance Theory, users' financial decisions are influenced by subjective risk perceptions, trust, and confidence rather than by objective technological performance (Ryu, 2018). Even technologically capable users may hesitate to adopt Fintech solutions if they perceive threats to data privacy or financial security, supporting Pavlou's (2003) assertion that trust and risk perceptions play a mediating role in digital adoption. At the same time, the absence of a significant impact of perceived benefit and user type suggests that adoption in emerging economies is more strongly constrained by perceived risks than driven by perceived benefits, especially in markets where institutional trust and regulatory assurance are still developing.

From a Technology Acceptance perspective, the results extend the understanding of post-adoption behavior by demonstrating that ease of use and usefulness—the central tenets of the Technology Acceptance Model (TAM)—are insufficient to explain user heterogeneity in Fintech adoption. Instead, E-Commerce Theory provides a broader lens to interpret these patterns, emphasizing the importance of trust, transaction transparency, and experiential value in digital financial engagement (Lee & Teo, 2015). This theoretical integration enriches the literature by positioning Fintech usage as a function of both technological acceptance and behavioral confidence, rather than as a purely rational response to perceived usefulness.

Practically, the study offers several implications. For policymakers, strengthening data governance and consumer protection mechanisms—through enhanced cybersecurity standards, mandatory data-disclosure protocols, and consumer complaint redress systems—could reduce perceived risk and foster confidence in digital finance. For Fintech providers, improving the visibility of security features, adopting transparent communication strategies, and developing user education initiatives can help convert cautious or late adopters into regular users. For users, particularly late adopters, structured awareness programs and peer learning networks could enhance digital financial literacy and confidence, bridging the behavioral gap in Fintech adoption.

Overall, the study contributes to the growing body of knowledge on Fintech adoption in emerging economies by demonstrating that risk perception, rather than technical capability, remains the dominant barrier to sustained usage. By integrating Behavioral Finance, E-Commerce, and elements of Technology Acceptance theories, this research provides a multidimensional understanding of Fintech adoption behavior, offering both theoretical advancement and practical direction for a more inclusive digital financial ecosystem in Sri Lanka.

Limitations and Future Research Directions

When considering the limitations of the study, the study only focuses on the top-line applications of Fintech, and applications such as blockchain, regtech, big data, machine learning, and artificial intelligence are not considered. These areas seem to have evolved globally, but the individual users are still at an evolving stage and in the context of the Sri Lankan Fintech infrastructure, are still at the infancy stage.

Another limitation of the study is that this study focuses on a limited sample size in Sri Lanka, due to the limited availability. and the infancy stage of different Fintech applications, obtaining a bigger sample size for the study might have provided a better understanding of the users' usage patterns and also provided a better understanding to identify if there are applications that are preferred and used by accounting professionals.

Future researchers may look into other areas of the study by combining blockchain, machine learning, and artificial intelligence, as they would provide a better understanding of the emerging technologies and whether they are being used by accounting professionals in Sri Lanka.

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