Banking Goes Digital: Unearthing the Adoption of Fintech by Bangladeshi Households

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Abstract

The underdeveloped financial system, large unbanked population, and rising mobile penetration rate in Bangladesh have ignited the development of innovative digital finance solutions. The increasing demand for Mobile Financial Services and other digital banking services has amplified Fintech adoption in Bangladesh. Thus, this paper aimed to assess the significant determinants of Fintech adoption by Bangladeshi households using a modified UTAUT2 model. Drawing on data collected from 481 Fintech users, CFA, and CV-SEM approaches were employed to classify the significant determinants concerning Fintech adoption in Bangladesh and a Multi-group analysis was performed to explore the moderating role of categorical variables. Although our findings reported insignificance of most of the UTAUT2 model's constructs, it revealed a significant impact of price value and moderating impact of gender, age, and education on Fintech adoption in Bangladeshi context. The findings reported significant insights on the pertinent theory which added new knowledge to the existent Fintech adoption literature. Since this is the first research on Fintech adoption in Bangladeshi context, it would have important theoretical, managerial, and policy implications.

Keywords: Fintech Adoption, Fintech in Bangladesh, Financial Inclusion, UTAUT2, Perceived Value, Structural Equation Modeling.

1. Introduction

In 2008, the US witnessed a massive financial crisis that eventually hit the rest of the world. Commercial banks have witnessed a deteriorating performance over the last 15 years. To generate additional profits, improve regulatory efficacy, and satisfy customers' requirements, the traditional financial markets had to introduce various Financial Technologies (Fintech) (Liu, Li & Wang, 2020). A voluminous literature has reported the essence of Fintech in the financial sector over the past decade (see Gomber, Koch, & Siering 2017; Minto, Voelkerling, & Wulff, 2017). Fintech scholars describe Fintech as the implementation of innovative technologies in the financial sector (Haddad & Hornuf, 2019). The global Fintech market has evolved dramatically in a brief amount of time due to rapid technological innovation.

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China and India are at top of the Global Fintech Adoption Index with a combined 87 percent (Ernst & Young, 2019). Since Fintech services have developed at an exponential pace in recent years, it is necessary to focus on their acceptability, reliability, and productivity. Our research, therefore, attempted to expand the extant Fintech scholarship by analyzing the major determinants of Fintech adoption in an emerging economy like Bangladesh.

Fintech is often considered as a game-changer when it comes to boosting financial inclusion in emerging economies (Senyo & Osabutey, 2020). Un(der)banked individuals can now access conventional banking benefits and lower-cost digital financial options due to mobile money (m-money) services, peer-to-peer (P2P) lending facilities, and mobile insurance (Vasiljeva & Lukanova, 2016). However, in Bangladesh, Fintech penetration has been limited to digital financial services (DFS) and mobile financial services (MFS), even though the global Fintech industry has progressed to a far more advanced level. Basing on a report published by the Bill & Melinda Gates Foundation, the financially included adult accounts for 47% of the country's population in Bangladesh in 2018. The MFS industry has grown in leaps and bounds, with 15 banks currently providing the services, and over 10 million average transactions daily as of April 2021 (Bangladesh Bank, 2021). This Fintech innovation has increased P2P transactions, inward remittance, salary payments (B2P), utility bill payments (P2B), merchant payments, and government payments (P2G). Hence, to assess its possible contribution to financial inclusion, it is critical to investigate the far-reaching potentials of Fintech in Bangladesh.

Given Fintech's widespread adoption and economic importance, several studies have been conducted to date to investigate its determinants. Despite this, a review of the extant literature indicates that Fintech findings are still incomplete since there is little understanding of how this technology is adopted in economies with varying levels of economic maturity. Developed countries were used as research contexts in the majority of Fintech studies (Haddad & Hornuf, 2019). In addition to this drawback, our review of the literature suggests that prior researches on technology adoption have mostly focused on older technologies like mobile money, M-commerce, and online gaming (Senyo & Osabutey, 2020). Since Fintech is such a new phenomenon, there have been few studies on its adoption in various socio-cultural contexts. Owing to lack of study in the emerging economies context, it can be argued that addressing this theoretical and empirical gap by integrating an emerging economy context like Bangladesh can significantly and interestingly expand the domain of Fintech adoption. Hence, our investigation on the adoption of Fintech innovations is confined to Bangladeshi context, to be specific to the households of Bangladesh. Bangladesh is showing remarkable progress towards achieving the sustainable development goals (SDGs) by 2030 and towards becoming a digital Bangladesh. (Datta & Rabbany, 2016). To achieve this goal, the country is focusing on Fintech development and financial inclusion to reach the unbanked population.

To address the a fore mentioned gaps in the extant studies, our research is guided by the broad research question: ‘What are the significant determinants that affect adoption of Fintech in Bangladesh?’ As a result, the broad objective of our study was to assess the Fintech adoption behaviour of Bangladeshi households. The specific objectives were: i) to examine the appropriateness of technology acceptance models in the context of Bangladesh ii) to unearth the significant determinants of Fintech adoption in Bangladesh. iii) to investigate the moderating role of demographic characteristics in adoption of Fintech innovation in Bangladesh. We examined the UTAUT2 theory of (Venkatesh, Thong, & Xu, 2012) by incorporating external factors in an emerging economy context. Hence, our paper extends the extant body of knowledge by addressing few gaps found in the Fintech adoption literature.

2. Literature Review

2.1 Prior Research on Fintech Adoption

Financial Technology (Fintech) covers a broad range of mobile applications, including payments, money transfers, loan requests, insurance transactions, wealth management, investment management, and crowdfunding (Puschmann, 2017; Chen, Wu, & Yang, 2019). Smartphones, cloud computing, artificial intelligence, machine learning, big data, and most recently, blockchain have reshaped the dynamics of Fintech in the financial system in terms of new opportunities, threats, and legal concerns (Puschmann, 2017; Chen et al., 2019; KPMG, 2019). The key fields of Fintech applications regarding these technological advances are banking and asset management, payments and connectivity, business operations and risk management, and data securitization and monetization (Puschmann, 2017; Chen et al., 2019).

Fintech services are becoming more widely available, opening up new business prospects for banks, non-banking financial firms, telecommunication companies, and retailers alike. Fintech adoption, on the other hand, is selective and can be attributed to several factors. Although ease of use affects the adoption of Fintech services, social influence has a negative effect, as per (Singh, Sahni, & Kovid, 2021). (Sing, Sahni, & Kovid, 2020) revealed that the main determinants affecting customers’ intention to use Fintech platforms are perceived usefulness and social influence, with social influence having a major negative effect. The authors reported that ease of use and social influence significantly affect actual use, but the behavioural intention and perceived usefulness do not. Besides, the perceived security by older users is strongly influenced by their age.

Ali et al., (2021) argued that perceived benefit and perceived risk by users have substantial and positive influences on Fintech adoption. Furthermore, perceived benefits have a major and positive influence on trust. Whereas, perceived risk by users has a negative and substantial effect on trust. There was also a clear positive and significant nexus between trust and the intention to use Islamic Fintech, according to the findings. An economy’s ICT competitiveness, particularly the political and regulatory environment, infrastructure, and firms' ICT use, all have a significant impact on Fintech adoption. Furthermore, demographic factors and socioeconomic status provide better support for understanding heterogeneity in Fintech service acceptance. (Krishna & Krishnan, 2020).

Several contextual factors including social influence, risk, and trust play a critical role in Fintech product adoption (Senyo & Osabutey, 2020; Kim et al., 2016). The majority of previous Fintech adoption literature, on the other hand, has concentrated on technical factors while ignoring social antecedents (Senyo & Osabutey, 2020; Shaikh et al., 2020). In mobile services literature, for example, technology adoption theories such as the technology acceptance model (TAM) was extensively used, (Kim et al., 2016; Senyo & Osabutey, 2020) while behavioural theories such as the unified theory of acceptance and use of technology (UTAUT) and the extended valence framework are yet underutilized. (Senyo & Osabutey, 2020; Abdullah, Rahman, & Rahim, 2018)

2.3 Unified Theory of Acceptance and Use of Technology

A significant number of alternative theories, such as diffusion of innovation (DoI) theory, and the model of personal computer utilization to describe the human acceptance of information technology~~,~~ appeared at the end of the twentieth century to overcome the shortcomings of the Technology Acceptance Model (TAM). This variety of contexts and theories provided technology adoption researchers with a new challenge of heterogeneity (Tamilmani, Rana, & Dwivedi, 2018). To address the shortcomings of existing theories, (Venkatesh, Morris, Davis, & Davis, 2003) constructed a systematic unified theory of acceptance and use of technology (UTAUT) founded upon the rigorous analysis of 8 dominant technology acceptance paradigms. Performance expectancy, effort expectancy, and social influence, according to UTAUT, are three direct determinants of behavioural intention that affect user behaviour when paired with supporting circumstances. The second most common theoretical lens for evaluating consumer mobile payment acceptance is UTAUT (Patil et al., 2017). Thus, different technology including Fintech adoption literature includes the UTAUT model for analyzing the significant determinants influencing adoption of Fintech worldwide.

Despite their scope and prominence, UTAUT-based theories have several underlying flaws (Tamilmani, Rana, & Dwivedi, 2020). Prior study has recognized shortcomings of UTAUT both directly and indirectly during their empirical investigations, as per (Dwivedi et al., 2019). When UTAUT is employed in an organizational context for technological adoption study, the pricing factors are ignored. (see Venkatesh et al., 2003). UTAUT2, on the other hand, is seen in the context of users who would pay for the use of technologies (Venkatesh et al., 2012). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2) is developed explicitly to explain technology adoption from the standpoint of the consumer. As a result, the UTAUT2 was chosen as a theoretical foundation for providing the conceptual model employed in our analysis in search of an adequate model addressing nearly all factors driving Fintech adoption by Bangladesh households. (Figure 1).

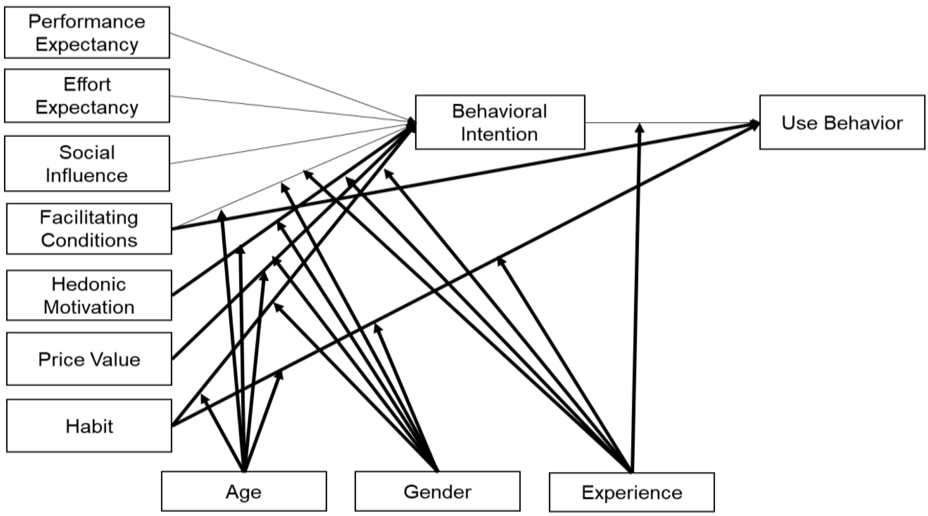

Figure 1: UTAUT2 Research Model of (Venkatesh, Thong, & Xu, 2012)

Previous research has investigated Fintech use by looking into people's intentions of using the technology (Rodrigues, Sarabdeen, & Balasubramanian, 2016). Given the widespread availability of Fintech facilities, few studies evaluate Fintech adoption by actual use. This study will use a modified UTAUT2 model by adding another significant construct to investigate the factors influencing Fintech adoption by Bangladeshi households.

3. Research Model and Hypothesis Development

We propose a modified UTAUT2 model basing on our extensive analysis of the literature. Our model incorporates 6 UTAUT2 constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and one additional construct- Perceived Risk (PR). The extant literature has investigated the impact of PR on Fintech usage (see Chopdar et al., 2018, Senyo & Osabutey, 2020) and identified the significance of PR on the adoption of the latest technologies (Ali et al., 2021). The Habit construct was excluded in our conceptual model since it demonstrates how addiction to a particular technology affects the actual usage in the long run. Since Fintech is a relatively recent technology in Bangladesh, the respondents of this study are in the early adoption stage. We tried to explore what determinants affect users' behavioural intention to accept a new technology rather than the impact of the habit of using it on the long-run adoption. Tamilmani et al., (2018) studied the appropriateness of the habit construct and examined 66 UTAUT2 based empirical studies. The author reported that 65% of the literature did not utilize the construct mostly because they aimed to investigate technology adoption among early-stage users. The UTAUT2 model incorporated different categorical variables as moderators, similarly, we examined the moderating role of gender, age, and education level in the relationship of the independent and dependent variables.

3.1 Performance Expectancy

As per (Venkatesh et al., 2012), PE can be defined as the extent to which one technology aids users in performing specific tasks. People are generally drawn to a technology that provides various advantages. When it comes to Fintech services, people are more willing to use the technology only if they can gain certain benefits from it. Though Fintech services are claimed to offer convenience, access to financial services, and faster transactions (Demirgüç-Kunt et al, 2018), its performance potential has yet to be thoroughly investigated in the study. Based on that the following hypothesis we propose:

H1: Performance expectancy affects Fintech adoption of Bangladeshi households.

H1a: Gender moderates the relation between performance expectancy and Fintech adoption.

H1b: Age moderates the relation between performance expectancy and Fintech adoption.

H1c: Education level moderates the relation between performance expectancy and Fintech adoption.

3.2 Effort Expectancy

The degree to which customers find it easy using one technology is measured by effort expectancy (EE) (Venkatesh et al., 2012). In general, EE assesses a technology's difficulty or ease of use. Ease of use is critical during the early stages of a technology's adoption because it impacts customer's willingness of using it (Kim et al., 2016). Prior research (e.g., Macedo, 2017; Venkatesh et al., 2003) has reported that EE and adoption of a technology have a positive relationship. Hence, our study hypothesizes that:

H2: Effort expectancy affects Fintech adoption of Bangladeshi households.

H2a: Gender moderates the relation between effort expectancy and Fintech adoption.

H2b: Age moderates the relation between effort expectancy and Fintech adoption.

H2c: Education level moderates the relation between effort expectancy and Fintech adoption.

3.3 Social Influence

Social influence (SI) can be referred to the extent to which others can persuade someone to accept new technology (Venkatesh et al., 2012). The impact of social knowledge, which works the same as social pressure to comply with claimed actions or opinions, has been identified in the literature (Fishbein & Ajzen, 1975). Since it is presumed that an individual discusses with his or her friends and peers about emerging technology and can be encouraged by their words, the impact of social norms is far greater for any cutting-edge innovation. As a result, important colleagues, friends, and family members' actions, comments, and perceptions about the use of technology are critical. SI is perhaps the most hypothesized and examined factor of UTAUT in the extant literature, and there has been an established positive relationship between SI and its impact on intention to adopt a technology. (See Rahi et al., 2019; Rodrigues et al., 2016). Thus our third proposed hypothesis is:

H3: Social influence affects Fintech adoption of Bangladeshi households.

H3a: Gender moderates the relation between social influence and Fintech adoption.

H3b: Age moderates the relation between social influence and Fintech adoption.

H3c: Education level moderates the relation between social influence and Fintech adoption.

3.4 Facilitating Conditions

Venkatesh et al. (2012) describe facilitating conditions (FC) as a customer's understanding of available support and resources while using one technology. Any technical breakthrough necessitates the use of resources such as computers, software, Internet connectivity, and specific skill sets. Customers who choose to use Fintech services must have a smartphone or a personal computer, as well as a network subscription, internet access, and the ability to operate the device and application. Hence, the availability of FC may generate increased concern for Fintech services and subsequent usage. Thus, the fourth hypothesis of this research is:

H4: Facilitating conditions affect Fintech adoption of Bangladeshi households.

H4a: Gender moderates the relation between facilitating conditions and Fintech adoption.

H4b: Age moderates the relation between facilitating conditions and Fintech adoption.

H4c: Education level moderates the relation between facilitating conditions and Fintech adoption.

3.5 Hedonic Motivation

Hedonic motivation (HM) as per (Venkatesh et al., 2012), refers to the enjoyment received while using one particular technology. When people like using a particular technology, it is almost certain that they will use it again. People, on the other hand, will not use technology if it does not please them. Hedonic motivation has shown mixed results in the existing literature on technology adoption. HM has been shown to positively influence the adoption of new technology in several studies (see Macedo, 2017; Venkatesh et al., 2012), but not in others (Baudier, Ammi, & Lecouteux, 2019). We propose to examine the impact of HM on Fintech adoption in Bangladesh. Thus it can be hypothesized that:

H5: Hedonic motivation affects Fintech adoption by Bangladeshi households.

H5a: Gender moderates the relation between hedonic motivation and Fintech adoption.

H5b: Age moderates the relation between hedonic motivation and Fintech adoption.

H5c: Education level moderates the relation between hedonic motivation and Fintech adoption.

3.6 Price Value

Price value (PV) refers to the cognitive trade-off between the user's gained benefits and the expense associated with using a particular technology (Venkatesh et al., 2012). In general, PV is higher when the advantages obtained outweigh the expense of using technology. Several pertinent pieces of literature show mixed results on the impact of PV on adopting an invention, like hedonic motivation. While some authors reported that the PV of technology has no impact on the intention to use it (Macedo, 2017; Oliveira et al., 2016), some argued that it has a positive impact on the intention to use technology (Venkatesh et al., 2012). Accordingly, we propose that:

H6: Price Value affects Fintech adoption by Bangladeshi households.

H6a: Gender moderates the relation between price value and Fintech adoption.

H6b: Age moderates the relation between price value and Fintech adoption.

H6c: Education level moderates the relation between price value and Fintech adoption.

3.7 Perceived Risk

The expectation of losses associated with the adoption of one technology is referred to as perceived risk (PR) (Pavlou, 2003). Due to the simulated existence of communications, most systems have inherent risk. Likewise, there is a chance of losing financial assets by using Fintech services. As a result, consumers are understandably reluctant to use Fintech apps. There are several aspects of PR in the digital world, including privacy, monetary, time, and opportunity costs (Featherman & Pavlou, 2003). The impact of PR on the use of Fintech services like mobile payments and mobile applications (Chopdar et al., 2018) has been studied in the past. Thus, the last hypothesis of this study is:

H7: Perceived risk affects Fintech adoption by Bangladeshi households.

H7a: Gender moderates the relation between perceived risk and Fintech adoption.

H7b: Age moderates the relation between perceived risk and Fintech adoption.

H7c: Education level moderates the relation between perceived risk and Fintech adoption.

Based on the hypotheses following research framework was developed. (Figure 2).

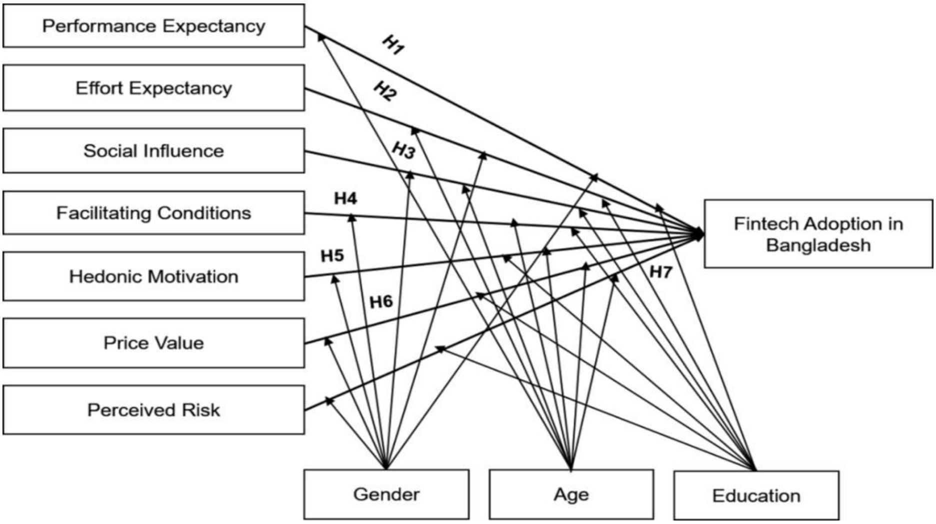

Figure 2: Research Framework

4. Research Method

4.1 Research Design

Fintech researchers frequently adopt two major types of research methods namely quantitative and qualitative. These approaches may be differentiated, as per (Bazeley, 2002), based on the form of data used, the inductive or deductive reasoning adopted, the type of inquiry (exploratory or confirmatory), the method of study (conceptual or empirical), and the approach to interpretation. The quantitative research method focuses on validating or rejecting predefined research hypotheses. The quantitative method mostly involves the 'what' type of questions. (Yin, 2003). In contrast, the qualitative method focuses on answering the 'why' or 'how' type of questions. (Yin, 2003). Prior Fintech studies demonstrate the use of both qualitative and quantitative research methods (Muthukannan et al., 2020; Singh et al., 2020). The study objectives (i.e. to test the hypotheses and theory), and the research question type ('what' type), suggests employing the quantitative method in this paper. Hence, we adopted a quantitative research design to test our developed hypotheses.

4.2 Measurement

The questionnaire of this research was constructed after a thorough analysis of relevant theoretical and empirical literature, with the study's objectives in mind. The questionnaire aimed at collecting primary data on the emergence of fintech services in Bangladesh as well as the adoption behaviour of fintech by Bangladeshi households. In this research, 30 scale items were used to measure the conceptual model's fundamental constructs. The key constructs of UTAUT2 (PE, EE, SI, FC, HM, PV, and BI) were assessed using the same elements that (Venkatesh et al., 2012) used to validate their new model (UTAUT2) along with an additional construct Perceived Risk (PR). The BI construct was renamed Fintech Adoption (FA) since the intention to perform a behaviour is the major predictor of the actual performance of that behaviour as per Theory of Reasoned Action. Thus, FA construct was utilized to analyze the behavioural intention of Bangladeshi users in terms of Fintech adoption. We used a seven-point Likert scale of the agreement to measure the respondents' responses on items of our modified UTAUT2 constructs. Finally, for demographic variables, six closed-ended questions were used: age, gender, education level, family income, most used Fintech, frequency of use.

4.3 Data Collection

Given that the study context of this research was Bangladesh, our target population was the Fintech users of Bangladesh. There was a requirement in this study to collect appropriate data that represents the population to accomplish generalization, as well as a necessity to choose a method that aligned with the research methodology. Given that we chose the convenience sampling technique for our data collection. This approach was chosen for two main reasons. First, convenience sampling is appropriate when large sample size is needed for generalization (Tsiotsou, 2015). Second, convenience sampling allows for the quick and easy assessment of items in a population via point of contact (Senyo & Osabutey, 2020). Before initializing the main data collection process, we pre-tested our questionnaire in two stages as outlined by (Shamsuddoha, 2004). At first, the primary version of the study questionnaire was thoroughly checked by two experts on the subject. In the following stage, we pre-tested the questionnaire by surveying 30 Fintech users among friends and family. Our main data collection started in February 2021 and ended after two months (April 2021). We conducted an online survey of Fintech users living in different regions of Bangladesh for this study using a self-administered questionnaire. The respondents were contacted through social media platforms. The inclusion criteria included a basic understanding of English language, and a minimum higher secondary level of education. 512 responses were collected online of which 481 seemed appropriate for recording and further investigation to verify the conceptual model and test the hypotheses.

4.4 Respondent's Profile

The demographic analysis of our surveyed Bangladeshi Fintech users is presented in Appendix A. The findings showed that 57.80% (278) of the respondents were male and 42.20% (203) were female users. The majority of the respondents aged between 18 to 23 years (38.05%), followed by 24 to 29 years (29.11%), 30 to 35 years (18.30%), 36 to 41 years (11.23%), and 41 or above the age (3.33%). The profiles suggest that the majority of the surveyed Fintech users were youth adults. The results showed that most of the Fintech users were Bachelor students (55.72%). 38.25% of the respondents had completed Master's Degree or above degrees. A small portion (6.03%) of the participants had attained higher secondary only. In terms of monthly family income, most of the participants (30.98%) belong to a middle-class family earning BDT 30,000 to 60,000 monthly, followed by people with a monthly income of BDT 60,000 to 90,000 (27.23%), followed by participants earning BDT 90,000 to 120,000 monthly (20.17%). 13.10% of the respondents earn BDT 120,000 to 150,000 monthly, whereas 8.52% had a monthly family income of more than BDT 150,000. Most of the participants had a Mobile Financial Service (MFS) account (85.03%). 45.11% of the respondents use internet banking sites and applications for banking services. The result demonstrates that 27.23% of respondents use different payment gateways, 13.51% use the QR payment system for purchasing products and services, 6.65% use EFT, and 5.41% use RTGS services. (Appendix A). In terms of frequency of use, most of the participants use Fintech services more than once a month (39.29%), followed by once a week (21.83%), more than once a week (15.80%), once a month (13.51%), daily (5.82%), once a year (2.29%) and 1.46% of the participants never used Fintech apps.

4.5 Test of Validity and Reliability

In both theoretical and empirical data collection contexts, understanding the terms-validity and reliability is important. As stated earlier, the validity of the study instrument was confirmed by pre-testing. A pre-test can identify problems with the instrument, items, and the overall data collection procedure. (Summerhill & Taylor, 1992). To test construct reliability, this study employed Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's alpha for each construct. The findings demonstrate that the CR values of the constructs range between 0.755 and 0.939 which exceeds our minimum cut-off value of 0.70 (Hair et al., 2010). The AVE which deals with the variance captured by the measures concerning measurement error, was greater than 0.50, indicating that the constructs were appropriate (Fornell & Larcker, 1981). For a scale and item to be considered reliable, the Cronbach's coefficient alpha score must be greater than 0.7 (Nunnally, 1978). The Cronbach's coefficient alpha score for each test used in this analysis is >0.70, according to Table (I). Hence, all the constructs of our study were reported to be reliable and valid for further analysis.

Table I: Test of Reliability and Validity

Constructs	Items	Loadings	CR	AVE	Cronbach's Alpha
Performance Expectancy	PE2	0.52	0.804	0.51	0.843
	PE3	0.72			
	PE4	0.84			
	PE5	0.75			
Effort Expectancy	EE1	0.87	0.857	0.61	0.820
	EE2	0.81			
	EE3	0.84			
	EE4	0.55			
Social Influence	SI1	0.91	0.917	0.79	0.823
	SI2	0.84			
	SI3	0.91			
Facilitating Conditions	FC1	0.82	0.910	0.72	0.910
	FC2	0.86			
	FC3	0.87			
	FC4	0.83			
Hedonic Motivations	HM1	0.78	0.838	0.72	0.753
	HM3	0.92			
Price Value	PV1	0.89	0.939	0.84	0.939
	PV2	0.92			
	PV3	0.93			
Perceived Risk	PR1	0.53	0.755	0.50	0.746
	PR2	0.63			
	PR3	0.75			
	PR4	0.72			
Fintech Adoption	FA1	0.91	0.821	0.70	0.815
	FA2	0.76			
Variance Explained by Harman's Single Factor Test					34.56%

4.6 Common Method Variance

We also conducted Harman's Single Factor test on the items to observe the existence of any common method variance (CMV). All the 30 questionnaire items were loaded onto a single factor. The new factor was not a part of our research framework, it was only introduced for the sake of analysis and discarded later. Table I presented that the percentage of variance explained by the common factor was reported as less than 50% (34.56%), suggesting that CMV was not present in the items (Eichhorn, 2014).

4.7 Data Analysis Technique

We recorded and analyzed the collected data using SPSS and AMOS software. We conducted both the descriptive and inferential statistical analyses in this research. We used the SPSS AMOS software to perform the Confirmatory Factor Analysis (CFA) and Covariance based Structural Equation Modeling (CV-SEM) to analyze the factors influencing user adoption of Fintech innovations in Bangladesh. The validity of the dataset was measured using Discriminant validity, and convergent validity. The reliability was measured with Composite Reliability (CR), Average Variance Extracted (AVE) and Cronbach's alpha (CA) to identify the influencing factors of fin-tech adoption in Bangladesh. We developed a measurement model that estimates the fit between our conceptual model and the dataset. The final stage of the statistical analysis tests the structural model by examining path coefficients, the impact of every hypothesized relation, and the explanatory strength of the study model as well. The measurement model and test of the hypothesis determined the significant determinants of Fintech adoption by Bangladeshi households. In the end, we also performed a multi-group analysis on AMOS to analyze the moderating impact of few categorical variables.

5. Results

5.1 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a theory-driven methodology that confirms a hypothesis. As a result, the theoretical relations among the observed and unobserved parameters direct the analysis plan (Schreiber et al., 2006). There are dozens of fit indices available to diagnose the goodness of fit in CFA, but only a few have been widely used. In this study, we used three types of model fits including absolute fit, incremental fit, and parsimonious fit. Several Fitness Indexes assess how well the hypothesized model fits the data. The model's value of fitness indexes has reached the degree of acceptance. Table II shows the overview of the model's fitness indexes.

Table II: Model Fit Indices and Their Acceptable Thresholds

Name of category	Fit Indices	Meaning	Value	Recommended Value
Absolute Fit	RMSEA	Root Mean Square of Error Approximation	0.08	RMSEA<0.08
	SRMR	Standardized Root Mean Square Residual	0.07	SRMR<0.08
Incremental Fit	CFI	Comparative Fit Index	0.90	CFI>0.90
	IFI	Incremental Fit Index	0.90	IFI>0.90
Parsimonious Fit	x^2/df	Relative Chi-Square	4.68	x^2/df <5.00
	PCFI	Parsimonious Comparative fit index	0.74	PCFI>0.50
	PNFI	Parsimonious Normed Fit Index	0.72	PNFI>0.50

Note: RMSEA<0.08 (Browne & Cudeck,1993); SRMR<0.08 (Hair et al., 2010); CFI>0.90 (Bentler, 1990); IFI>0.90 (Bentler & Bonett, 1980); x^2/df <5.00 (Marsh & Hocevar,1985); PCFI>0.50, PNFI>0.50 (Mulaik et al., 1989)

Absolute fit indices (McDonald & Ho, 2002) assess how well a priori model matches the sample data and show which hypothesized model has the best fit. To measure the absolute fit, Root Mean Square of Error Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) were calculated using AMOS. Both the fit indices were under acceptable limits (Browne & Cudeck,1993; Hair et al., 2010). Incremental fit indices, also called Relative fit, involves a factor that shows deviations from a null model. Thus, these are often called comparative indices. Table III shows that the Incremental fit indices (CFI, NFI) of the model represent a good model fit. Finally, the parsimonious fit indices (x2/df, PCFI, PNFI) represent superior model fit. All these goodness of fit indices are well above the generally acceptable levels, indicating the structural model fits well. As a result, it can be documented that our Fintech adoption measurement scale has a strong model fit.

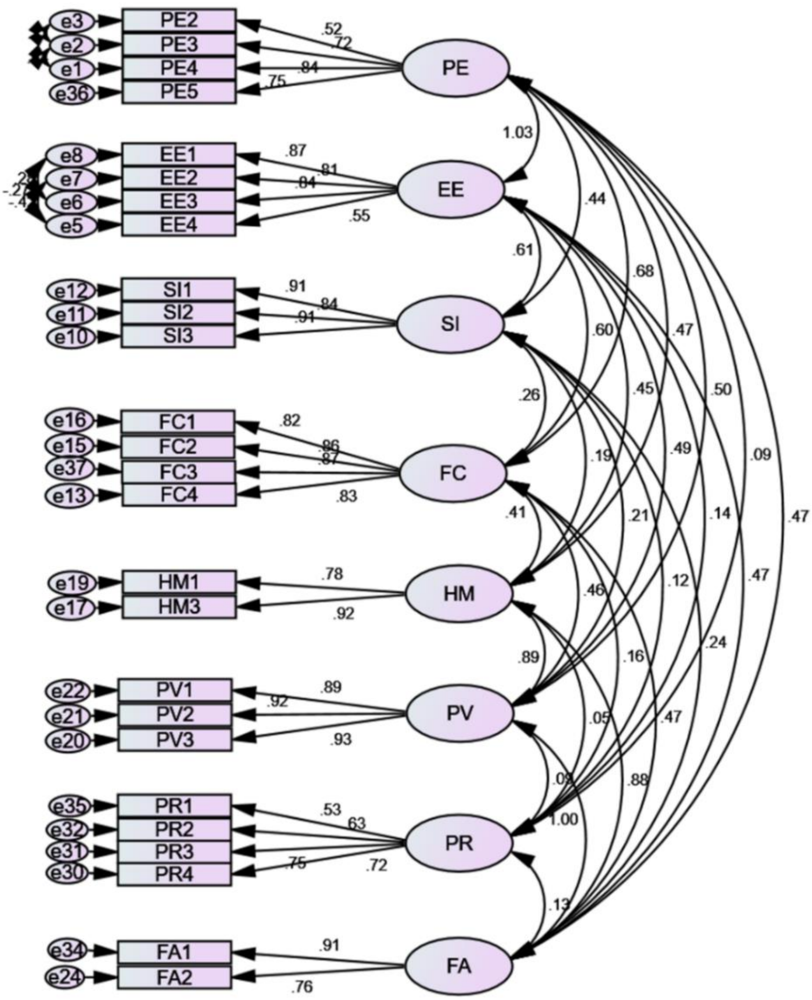

Figure 3: Measurement Model

5.2 Measurement Model

We developed an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) measurement theory including 8 latent constructs to investigate the significant factors concerning users' Fintech adoption in Bangladesh. (Figure 3). The CFA model showed that the eight latent constructs in this research are PE, EE, SI, FC, HM, PV and PR. The PE1-PE5, EE1-EE4, SI1-SI4, FC1-FC4, HM1-HM3, PV1-PV3, PR1-PR4 represent the measured independent variables and the values associated with them (factor loadings) indicate the relationship between the unobserved factors and the observed variables. To get construct validity and a better model fit, items with lower standard factor loadings (less than 0.50) were eliminated from the model. (Hair et al., 2012). The four excluded measurement items are PE1, SI4, HM2, FE3. The rest of the 26 items were retained in the measurement model for SEM.

5.3 Covariance Based Structural Equation Modeling (CV-SEM)

The covariance-based structural equation modeling (CV-SEM) technique was employed in this research using the SPSS AMOS software. (Figure 4). The relationship between the seven latent constructs and Fintech Adoption (FA) construct in our CFA model was illustrated by curved arrows that indicate a correlational relationship. In the structural model (Figure 4) the relation is converted into a dependence relationship and presented with a single-headed arrow. These single-headed arrows towards the FA construct are similar to the relationship that represents a multiple regression model and is measured by a regression coefficient. The structured model shows that the R square value associated with the FA construct is 1.00 indicating the 7 latent constructs explain 100% variance of the Fintech Adoption variable.

Table III: Path Coefficients of Fintech Adoption Factors

	Estimate	S.E.	C.R.	P	Supported/Not Supported
Fintech Adoption<--- Performance Expectancy	-.008	.109	-.069	.945	Not Supported
Fintech Adoption<--- Effort Expectancy	-.082	.146	-.563	.574	Not Supported
Fintech Adoption<--- Social Influence	.045	.028	1.589	.112	Not Supported
Fintech Adoption<-- Facilitating Conditions	.026	.039	.674	.500	Not Supported
Fintech Adoption<--- Hedonic Motivation	-.046	.062	-.731	.465	Not Supported
Fintech Adoption<--- Price Value	.874	.069	12.589	***	Supported
Fintech Adoption<--- Perceived Risk	.045	.033	1.366	.172	Not Supported
R Square				1.00	

The path coefficients of the SEM identified that only Price Value significantly affects the Fintech adoption by Bangladeshi households. (*β=0.874, p=.000)*. Thus, H6 is accepted. But the other 6 latent variables Performance Expectancy (*β=-0.008, p=.945)*, Effort Expectancy (*β=-0.082, p=.574)*, Social Influence (*β =0.045, p=.112)*, Facilitating Conditions (*β=0.026, p=.500)*., Hedonic Motivations (*β=-0.046, p=.465)*, and Perceived Risk (*β=0.045, p=.142)* were found to have an insignificant relationship with customers' adoption of Fintech services in Bangladesh. (Table III).

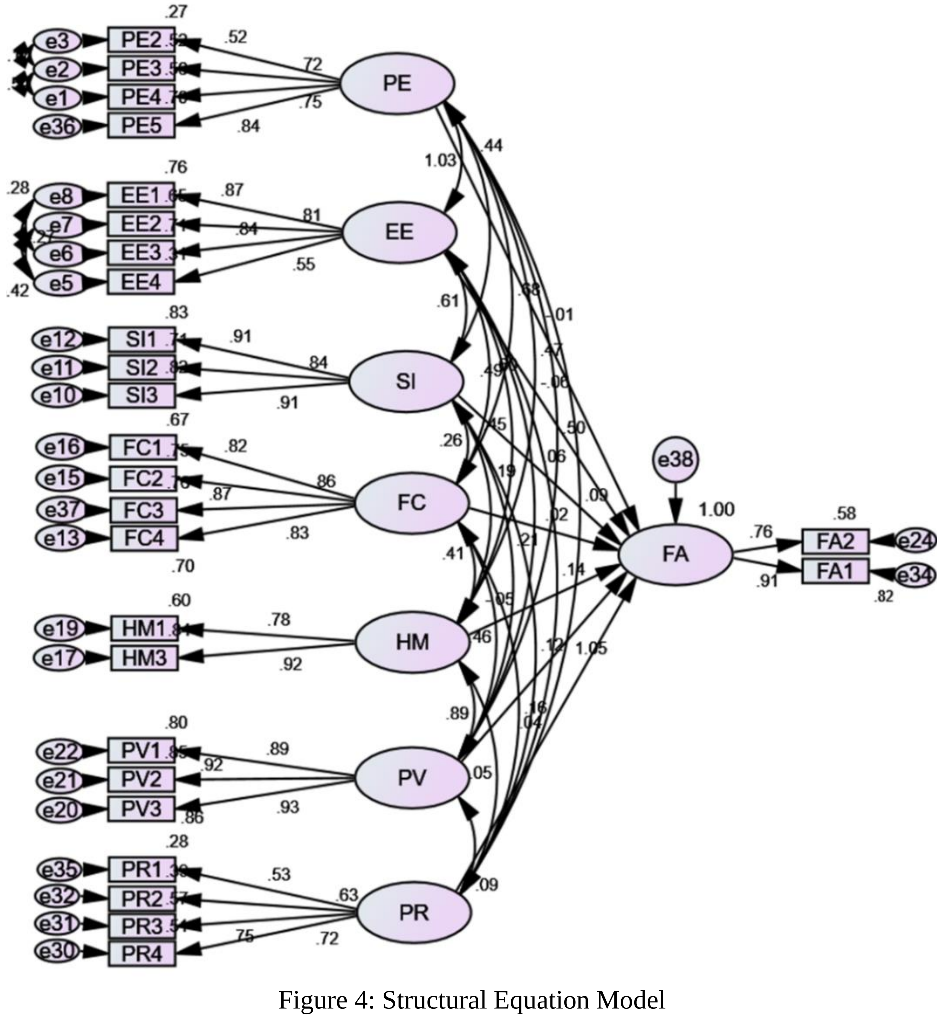

Figure 4: Structural Equation Model

Hence, H1, H2, H3, H4, H5, and H7 are rejected based on their p-value which is not significant at a 5% significance level (*p>0.05)*. The result of hypothesis testing is illustrated in Table IV. It can be concluded that the UTATUT constructs except the PV do not have a significant effect on FA in Bangladesh. The findings of the model differ from technology to technology and country to country.

Table IV: Results of Relationships

	Hypotheses	Decision
H1	Performance expectancy affects Fintech adoption of Bangladeshi households	Rejected
H2	Effort expectancy affects Fintech adoption of Bangladeshi households	Rejected
H3	Social influence affects Fintech adoption of Bangladeshi households	Rejected
H4	Facilitating conditions affect Fintech adoption of Bangladeshi households.	Rejected
H5	Hedonic motivation affects Fintech adoption by Bangladeshi households.	Rejected
H6	Price Value affects Fintech adoption by Bangladeshi households.	**Accepted**
H7	Perceived risk affects Fintech adoption by Bangladeshi households	Rejected

5.4 Moderating Role of Categorical Variables

We conducted a multi-group analysis to assess if respondents' gender, age, and level of education moderate the relation between the study constructs. The output of the analysis is presented in Appendix B, C, and D. The findings suggested that gender moderates the relations between SI and FA, FC, and FA, thus H3a and H4a are accepted. Another categorical variable age was found to moderate the relationships between PV and FA, PR and FA. Hence, we can accept H6b and H7b. We examined the moderating impact of the level of education in the relationships and observed that education level moderates the relation between PV and FA, PR, and FA. Thus, we can accept H6c and H7c. The rest of the hypotheses are rejected since gender, age, and education level do not moderate the other relationships. (Table V).

Table V: Results of Moderating Relationships

	Hypotheses	Decision
H1a	Gender moderates the relation between performance expectancy and Fintech adoption.	Rejected
H1b	Age moderates the relation between performance expectancy and Fintech adoption.	Rejected
H1c	Education level moderates the relation between performance expectancy and Fintech adoption.	Rejected
H2a	Gender moderates the relation between effort expectancy and Fintech adoption.	Rejected
H2b	Age moderates the relation between effort expectancy and Fintech adoption.	Rejected
H2c	Education level moderates the relation between effort expectancy and Fintech adoption.	Rejected
H3a	Gender moderates the relation between social influence and Fintech adoption.	**Accepted**
H3b	Age moderates the relation between social influence and Fintech adoption.	Rejected
H3c	Education level moderates the relation between social influence and Fintech adoption.	Rejected
H4a	Gender moderates the relation between facilitating conditions and Fintech adoption.	**Accepted**
H4b	Age moderates the relation between facilitating conditions and Fintech adoption.	Rejected
H4c	Education level moderates the relation between facilitating conditions and Fintech adoption.	Rejected
H5a	Gender moderates the relation between hedonic motivation and Fintech adoption.	Rejected
H5b	Age moderates the relation between hedonic motivation and	Rejected

	Fintech adoption.	
H5c	Education level moderates the relation between hedonic motivation and Fintech adoption.	Rejected
H6a	Gender moderates the relation between price value and Fintech adoption.	Rejected
H6b	Age moderates the relation between price value and Fintech adoption.	**Accepted**
H6c	Education level moderates the relation between price value and Fintech adoption.	**Accepted**
H7a	Gender moderates the relation between perceived risk and Fintech adoption.	Rejected
H7b	Age moderates the relation between perceived risk and Fintech adoption.	**Accepted**
H7c	*Education level moderates the relation between perceived risk and Fintech adoption.*	**Accepted**

6. Discussion

This research has developed seven hypotheses after an extensive review of pertinent literature. After statistically analyzing the data from the Fintech users, only one hypothesis (H6) was supported and proved to affect the adoption of Fintech services. The factor that was found to significantly impact the Fintech adoption behaviour in Bangladesh is Price Value (PV), which is also found in existing technology adoption theories. (Davis, Bagozzi, & Warshaw, 1989; Venkatesh et al., 2012). Furthermore, our analysis rejected six hypotheses derived from UTATUT2 model, as the PE, EE, SI, FC, HM, and PR factors proved to be not significantly associated with the adoption of Fintech in Bangladesh. This output was expected to an extent since this research examined the adoption of Fintech innovations in Bangladesh, a context that has not yet been addressed in prior literature. Besides, prior technology adoption studies argue that different technological and cultural contexts produce different constructs concerning the adoption of a specific technology. (Gefen, Karahanna, & Straub, 2003).

Our CV-SEM analysis demonstrated that PE does not have a positive association with Fintech adoption by Bangladeshi households. The finding is consistent with a series of Fintech literature (Abdullah et al., 2018; AbuShanab & Pearson, 2007), where the authors found that PE does not significantly affect Fintech adoption. Besides, according to few technologies related studies, technology has value for consumers even though its performance is still inferior to its rivals. (See Slade, 2015). These contradicting findings suggest that culture and country differences play an integral part in the relationship of the UTAUT model constructs. Different external variables which include the cost of the service, countrywide availability may outweigh the performance of the technology in the Bangladeshi context. For instance, in the case of MFS, the existing MFS providers in Bangladesh (bKash, Nagad, Rocket) have almost similar services, but their customer acquisition may get affected by the number of agents available, cost of transactions, cash-out charge. Hence, it can be concluded that PE can be insignificant based on country differences depending on the characteristics of the customers. We also found Effort Expectancy (EE) to have a relatively insignificant association with Fintech adoption of Bangladeshi users, which contradicts a few existing technology adoption research (Chong, 2013; Davis et al., 1989). Nonetheless, these findings are similar to a few prior technological acceptance studies that documented an insignificant association between EE and users' intention of adopting one technology. (Miladinovic & Hong, 2016). (Muhsin, Thomas, & Nurkhin, 2016) established that the majority of the young technology users do not consider ease of using the apps will influence their adoption since they are already accustomed to using numerous information technologies. Thus, ease of use may have significance to the rural and less-educated users, however, it may not be significant to urban technology users in terms of Fintech adoption.

The findings from our statistical analyses reported that SI does not significantly impact the Fintech apps adoption. Prior Fintech literature that focused on mobile application adoption found that SI did not impact the adoption of mobile applications, which supports our claim. (Miladinovic & Hong, 2016; Yang, 2013). The reason could be the availability of thousands of app reviews and expert opinions. The SEM result also reported that FC does not have a significant positive relation with Fintech adoption in Bangladesh. Thus, it indicates that device and information availability do not impact Fintech app adoption by Bangladeshi households. The reason could be the widespread smartphone and internet penetration in the country in recent years. If someone does not have a smartphone, he or she at least has one Symbian or java phone at home that can be used for mobile banking. MFS of Bangladesh like bKash, Rocket, Nagad does not require a smartphone for mobile banking service. Thus, one can easily make a transaction by dialing with their Symbian or java phone.

Our analysis concluded that HM has an insignificant effect on FA in Bangladeshi households. (Handoko, 2020) argued that the young generation is not much hedonic. Thus, HM does not significantly affect their technology adoption. A few prior series of literature on technology adoption also support this result. (See Palau-Saumell et al., 2019). Although this result contradicts the prior technology adoption literature (Yang, 2010), those studies were conducted on different technologies and in a different socio-cultural context. In consumer behaviour literature, researchers conceptualized the monetary cost and product quality to assess customers' perceived value (PV) of that specific product. (see Zeithaml, 1988). PV is positive when the perceived benefits from that product exceed the costs incurred by the customers to avail that product. Customers intend to adopt a new technology only when the value generated by the product is worth their spent money (Handoko, 2020). PV has been proven to significantly affecting the adoption of Fintech apps by Bangladeshi households in this paper, which confirms the findings of (Dodds, Monroe, & Grewal, 1991; Palau-Saumell et al., 2019).

We integrated the perceived risk (PR) construct into our research model by reviewing the recent empirical literature on the adoption of the latest technologies. The statistical analysis documented that PR has an insignificant effect on the customers' adoption of Fintech applications. This result is supported by the findings of another Fintech literature (Al-Saedi et al., 2020), but this study focused only on M-payment. Nonetheless, the findings contradict the existing tech adoption literature. (Slade et al., 2015; Chen, 2008). PR is concerned with privacy and transaction security for the customers. In the case of Fintech services in Bangladesh, in many fraudulent cases, identity theft is reported regularly. But in most incidents, it occurs due to the customer's ignorance and negligence as they get manipulated and provide their identity and account information to the hackers and frauds. The adoption of Fintech applications is growing since the security from the providers' end is quite strong and very few fraud cases are reported due to the service providers' faults. Hence, further research is necessary for the Bangladeshi context to identify the impact of PR on Fintech adoption.

We also tested the moderating impact of few demographic characteristics (gender, age, and education) on the relationships between our latent and observed constructs. The multi-group analysis revealed the moderating impact of these categorical variables in some of the relationships. The results documented that the male users are subject to social influence or peer pressure while adopting a particular technology. On the other hand, facilitating condition plays a pivotal role for the female users while adopting Fintech apps. We found that although Fintech adoption in Bangladesh is significantly driven by the perceived value factor, it is not a significant determinant for people above 41 years of age. In terms of education level, users with a Higher secondary degree do not bother much about perceived value while adopting Fintech. The analysis also revealed that customers with a master's degree or above are more concerned about perceived risk (PR) than others. (See Appendix B, C & D).

6.1 Theoretical Implications

The first and foremost contribution of our paper is the development and further analysis of a modified UTATUT2 model in an emerging economy perspective that incorporates the Perceived Risk (PR) construct. As mentioned earlier, these constructs are grounded in the Technology Acceptance Theory, Consumer Behaviour theory. Combining these theoretical models allows this research to offer a holistic understanding of Fintech adoption intention in an emerging economy like Bangladesh.

The findings of this paper demonstrate that only the Perceived Value factor tends to exert a significant impact on Fintech adoption by Bangladeshi households. Thus, in line with several studies, this study identifies that the findings from the UTAUT2 theoretical framework are subjective to different technologies and socio-cultural contexts. (Handoko, 2020; Palau-Saumell et al., 2019; Al-Saedi et al., 2020). Given the Bangladeshi context, our paper adds to the extant body of knowledge since it addresses few gaps found in the Fintech adoption literature.

Secondly, our study adds contributions to the technology adoption knowledge by supporting that PV has a significant relationship with technology acceptance. (Palau-Saumell et al., 2019, Jensen, 2012; Dodds et al., 1991). It is evident that consumers in low-income households in Bangladesh are relatively price-sensitive, and are willing to avail of local services at an affordable price (DATABD, 2018). Since MFS is the most used Fintech service in Bangladesh and a large portion of the users are from lower and middle-income households, the cost of the service plays the most crucial role in customers' adoption of that service. As a result, this study contradicts some prior technology adoption literature because of the technological and socio-cultural differences. Thus, we recommend extensive future research in this field in the context of Bangladesh.

6.2 Practical Implications

Our findings have substantial practical implications in addition to the mentioned theoretical contributions. This paper emphasizes the importance of price value as a factor in deciding whether or not to use Fintech services in Bangladesh. The study finds that PV is the most crucial antecedent, implying that customers would continue to use Fintech services if the providers deliver the best price value. The utility that consumers get from the service in exchange for their money is referred to as price value. Banks and other Fintech service providers should use this knowledge to develop and promote their Fintech offerings to increase user acceptance and usage. Furthermore, our study identified that mobile banking or mobile financial service (MFS) is the most used Fintech service in Bangladesh. MFS has a higher customer acceptance and usage than internet banking, RTGS, EFT, and QR-based payment services. As the economy aims to be cashless in the future, different industries such as restaurants, hotel-tourism, transport, ride-hailing, e-commerce can use these Fintech services for transactions. Fintech adoption will lessen both the time and cost for most of the service industries. The Fintech service providers should introduce the latest technologies to reach the financially excluded population at an affordable price.

6.3 Limitations and Future Research Direction

Although the study offers valuable insights that advance the understandings, development, and adoption of Fintech innovations in Bangladesh, this study has few limitations too. First, despite having a widespread acceptance and implementation of UTATUT2 theory in technology adoption literature, this study argued that most of the model constructs insignificantly affect Fintech adoption in Bangladesh. Since this is the first research on Fintech adoption behaviour in Bangladesh further research can be conducted in a similar context to support or contradict the present study. Second, the current research centered only on Fintech service end-users. Understanding the viewpoints of the intermediaries such as merchants and agents would be beneficial since the MFS industry employs thousands of agents who play an integral role in the delivery of the services. Finally, future scholars can also explore the mediation and moderation of other factors in this model since there exists a significant literature gap in the case of Fintech service adoption in an emerging economy context.

7. Conclusion

Fintech advancements in recent years have made it easier than ever for consumers to access financial markets and services. Several studies have been carried out to identify the factors influencing Fintech adoption in developed countries. But very little prior research has focused on the emerging economies and none of them focused on the Fintech adoption in Bangladesh. Thus, this study addresses few knowledge gaps in the extant Fintech literature by evaluating the significance of an extended UTATUT2 constructs in determining the consumers' adoption of Fintech service. Along with six latent constructs from the UTAUT2 model, this study incorporated another construct from recent empirical literature namely Perceived Risk (PR). CFA was performed to test the fitness of our developed research model. The CFA result and the model fit indices reported a good model fit to the dataset. We conducted a Covariance-based Structural Equation Modeling (CV-SEM) to identify the significant determinants influencing Fintech adoption in Bangladeshi households. The findings documented that only the price value construct had a significant association with the Fintech adoption in Bangladesh thus proving that the UTAUT2 measurement theory is subject to technological and socio-cultural contexts. Since the lower class and middle-class consumers in Bangladesh are mostly price-sensitive, this finding is justified. Our analysis also reported the moderating role of gender, age, and education level of Bangladeshi customers in their Fintech adoption intention. Researchers, Fintech service providers, and policymakers will benefit greatly from the findings of this study. The contributions of this research, in particular, are numerous and can be classified as contributions to theory, policy, and practice.

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Appendix

Appendix A: Respondents' Profile

	Frequency	Percent	Valid Percent	Cumulative Percent
		Gender		
Male	278	57.80	57.80	57.80
Female	203	42.20	42.20	100
Total	481	100	100	
		Age		
18 to 23	183	38.05	38.05	38.05
24 to 29	140	29.11	29.11	67.15
30 to 35	88	18.30	18.30	85.45
36 to 41	54	11.23	11.23	96.67
41 or above	16	3.33	3.33	100
Total	481	100.00	100	
		Level of Education		
Higher Secondary	29	6.03	6.03	6.03
Bachelor	268	55.72	55.72	61.75
Master Degree or Above	184	38.25	38.25	100
Total	481	100	100	
		Monthly Family Income		
30,000-60,000	149	30.98	30.98	30.98
60,000-90,000	131	27.23	27.23	58.21
90,000-120,000	97	20.17	20.17	78.38
120,000-150,000	63	13.10	13.10	91.48
More than 150,000	41	8.52	8.52	100
Total	481	100.0	100	
Which of the Fintech services you mostly use for monetary transactions? (Multiple Choice)				
Internet Banking	217	45.11	45.11	

Mobile Financial Services	409	85.03	85.03	
RTGS	26	5.41	5.41	
EFT	32	6.65	6.65	
QR Payment System	65	13.51	13.51	
Payment Gateways	131	27.23	27.23	
Total	481	100.0	100	
How Frequently Do you Use Fintech?				
Daily	28	5.82	5.82	5.82
More than once a week	76	15.80	15.80	21.62
Once a week	105	21.83	21.83	43.45
More than once a month	189	39.29	39.29	82.74
Once a month	65	13.51	13.51	96.26
Once a year	11	2.29	2.29	98.54
Never	7	1.46	1.46	100
	481	100	100	

Appendix B: Moderating Impact of Gender

			Estimate	S.E.	C.R.	P
		Male				
FA	<---	PE	.032	.101	.313	.754
FA	<---	EE	-.097	.117	-.828	.408
FA	<---	SI	.072	.037	1.942	**.050**
FA	<---	FC	-.064	.056	-1.146	.252
FA	<---	HM	-.104	.083	-1.244	.213
FA	<---	PV	.888	.105	8.483	***
FA	<---	PR	.045	.038	1.175	.240
		Female				
FA	<---	PE	-.136	.223	-.609	.543
FA	<---	EE	.056	.388	.144	.886
FA	<---	SI	.013	.042	.314	.753
FA	<---	FC	.121	.057	2.133	**.033**
FA	<---	HM	.037	.105	.350	.727
FA	<---	PV	.868	.091	9.494	***
FA	<---	PR	.037	.060	.608	.543

Appendix C: Moderating Impact of Age

			Estimate	S.E.	C.R.	P
		18-21 Years				
FA	<---	PE	.174	.120	1.456	.145
FA	<---	EE	-.245	.161	-1.521	.128
FA	<---	SI	.012	.039	.300	.764
FA	<---	FC	-.021	.064	-.336	.737
FA	<---	HM	.007	.110	.061	.951
FA	<---	PV	.780	.115	6.774	***

			Estimate	S.E.	C.R.	P
		18-21 Years				
FA	<---	PR	.032	.046	.711	.477
		24-29 Years				
FA	<---	PE	-.163	.116	-1.402	.161
FA	<---	EE	.135	.183	.736	.461
FA	<---	SI	.031	.049	.623	.534
FA	<---	FC	.116	.072	1.610	.107
FA	<---	HM	-.091	.111	-.820	.412
FA	<---	PV	.816	.115	7.090	***
FA	<---	PR	.129	.075	1.726	.084
		30-35 Years				
FA	<---	PE	-.079	.638	-.123	.902
FA	<---	EE	-.059	.638	-.093	.926
FA	<---	SI	.133	.159	.832	.405
FA	<---	FC	-.107	.129	-.829	.407
FA	<---	HM	.086	.167	.512	.609
FA	<---	PV	.944	.214	4.414	***
FA	<---	PR	-.037	.100	-.374	.708
		36-41 Years				
FA	<---	PE	-.237	.231	-1.028	.304
FA	<---	EE	.418	.391	1.069	.285
FA	<---	SI	-.105	.089	-1.174	.240
FA	<---	FC	.082	.101	.808	.419
FA	<---	HM	.053	.121	.435	.664
FA	<---	PV	.830	.150	5.523	*******
FA	<---	PR	.158	.068	2.319	**.020**

			Estimate	S.E.	C.R.	P
		18-21 Years				
		41 or above				
FA	<---	PE	.076	4.743	.016	.987
FA	<---	EE	.003	1.011	.003	.998
FA	<---	SI	.034	2.698	.013	.990
FA	<---	FC	.155	.997	.156	.876
FA	<---	HM	1.180	16.277	.072	.942
FA	<---	PV	-.076	15.935	-.005	**.996**
FA	<---	PR	.022	1.286	.017	.986

Appendix D: Moderating Impact of Education Level

			Estimate	S.E.	C.R.	P
		Higher Secondary				
FA	<---	PE	-.187	2.685	-.070	.945
FA	<---	EE	.266	2.725	.098	.922
FA	<---	SI	-.114	.644	-.177	.860
FA	<---	FC	.152	.570	.266	.790
FA	<---	HM	.021	.800	.027	.979
FA	<---	PV	.712	.759	.939	**.348**
FA	<---	PR	-.024	.452	-.053	.958
		Bachelor				
FA	<---	PE	.083	.087	.952	.341
FA	<---	EE	-.152	.114	-1.334	.182
FA	<---	SI	.041	.031	1.338	.181
FA	<---	FC	-.030	.052	-.571	.568
FA	<---	HM	-.054	.089	-.605	.545

			Estimate	S.E.	C.R.	P
			Higher Secondary			
FA	<---	PV	.852	.094	9.103	***
FA	<---	PR	.005	.042	.108	.914
			Masters or above			
FA	<---	PE	-.802	.720	-1.115	.265
FA	<---	EE	1.084	1.160	.934	.350
FA	<---	SI	-.064	.131	-.491	.624
FA	<---	FC	.079	.083	.949	.343
FA	<---	HM	.020	.139	.140	.889
FA	<---	PV	.858	.153	5.598	***
FA	<---	PR	.144	.072	2.014	**.044**