The Dynamics of Fintech Adoption Among Bangladeshi Youth: A UTAUT2 Model Perspective

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ARTICLE INFO

Keywords: Fintech Adoption, Performance Expectancy, Social Influence, Trust, UTAUT2, Theory of Planned Behavior

RECEIVED
3 September 2024

ACCEPTED
22 December 2024

PUBLISHED
31 August 2025

DOI
https://doi.org/10.5281/zenodo.17240168

ABSTRACT

Bangladesh's rapid economic progress and technological advancement have significantly impacted its financial technology (fintech) sector. This study investigates the factors influencing fintech adoption among Bangladeshi youth, employing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model and the Theory of Planned Behavior. The findings reveal that Performance Expectancy, Facilitating Conditions, and Trust positively influence fintech adoption intention, highlighting the importance of user-friendly, reliable, and secure fintech solutions. Interestingly, Social Influence negatively impacts adoption intention, suggesting skepticism towards peer recommendations. The study also finds that Effort Expectancy and Hedonic Motivation do not significantly affect adoption intention, indicating a focus on practicality and utility over ease of use and enjoyment. Service Quality significantly impacts User Behavior, emphasizing the need for high-quality customer service to maintain user engagement. These insights provide valuable guidance for fintech companies aiming to enhance adoption and user satisfaction by focusing on critical factors influencing user perceptions and behaviors. This research expands the UTAUT2 model by incorporating information quality and willingness to pay, offering a comprehensive framework for understanding fintech adoption in developing countries like Bangladesh. Overall, the study enhances the theoretical framework of FinTech adoption by integrating context-specific variables and providing empirical evidence from a developing country perspective.

In practical, FinTech companies should invest in customer service training and infrastructure to deliver a positive user experience, fostering long-term user retention.

1. Introduction

Bangladesh's economic progress is increasingly linked to its technological infrastructure, particularly in the realm of financial technology (fintech). Fintech combines finance and advanced technology to enhance financial transactions, making them more accessible and efficient. This fusion involves not only technology and processes but also ecosystems that facilitate smoother commercial activities, including payments, lending, stock trading, and currency exchanges (Venkatesh & Brown, 2001). Over recent years, Bangladesh has experienced significant digital growth. By 2024, the country has seen a substantial increase in digital engagement, with internet usage growing significantly. The number of smartphone users has also increased, mirroring this digital expansion (Alalwan et al., 2017). By 2020, the Bangladeshi economy was valued at around $85–90 billion and is forecasted to skyrocket to $800 billion by 2030. Factors such as enhanced digital access, rising incomes, and a burgeoning youth population contribute to this growth (World Bank, 2021). Additionally, the post-COVID-19 era has positioned Bangladesh as a key player in the fintech sector, only second to the United States in terms of market potential (Andersen & Jakobsen, 2018).

According to the World Bank Findex Report 2021, a significant portion of adults in Bangladesh remain unbanked, and many do not use technology for financial transactions. Challenges include poor information quality, high service fees, inaccessible banking services, and low trust in financial institutions (World Bank, 2021). Addressing these issues is critical for the adoption of fintech solutions among Bangladeshi youth. This is particularly important as the country's financial sector evolves through innovations such as green finance and technologies that promote sustainable practices. Moreover, the pandemic has forced people to rely more on digital technologies, significantly altering consumer behavior towards fintech (Firmansyah et al., 2022; Venkatesh et al., 2012). The government's initiatives, like the Digital Bangladesh Mission, aim to enhance internet connectivity and foster a tech-savvy environment. The upcoming introduction of 5G technology is expected to revolutionize the fintech landscape in Bangladesh, similar to trends observed in the global south (Rahman et al., 2020). Despite significant advancements in financial technology, studies exploring fintech adoption in Bangladesh are scarce, particularly those focusing on youth. Existing research often overlooks the interplay of social and contextual factors unique to developing countries. This study bridges this gap by applying UTAUT2 and TPB frameworks to examine fintech adoption among Bangladeshi youth, incorporating localized variables like information quality and readiness to pay for services.

This study integrates the Theory of Planned Behavior to analyze how the younger generation in Bangladesh interacts with fintech. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Theory of Planned Behavior (TPB) are widely used frameworks for understanding user behavior and technology adoption. Meanwhile, TPB emphasizes the role of attitudes, subjective norms, and perceived behavioral control in predicting intentional behavior, offering insights into how external influences and individual perceptions shape decision-making. Integrating these models provides a comprehensive lens for analyzing technology acceptance and user behavior dynamics. Considering the dynamic socio-economic factors unique to Bangladesh, this research adds new dimensions to the model by including information quality and readiness to pay for services. These additions aim to better understand the link between consumer intentions and fintech adoption, thereby enriching the fintech literature and guiding marketers in developing targeted strategies to tap into the untapped potential within this sector (Ajzen, 1991).

2. Theoretical Framework and Hypothesis Development

The UTAUT model, initially proposed by (Venkatesh & Brown, 2001), serves as a foundational theoretical framework aimed at explaining and predicting user engagement with technology. In order to better explain technology adoption, this model synthesizes components from earlier models and emphasizes four key factors: performance expectancy, effort expectancy, social impact, and facilitating conditions. The same authors released an improved version of UTAUT2 in 2012, adding to the framework with new components like price value, habit, and hedonic motivation. These components help to further elucidate the comprehensive dynamics of technology usage. The model suggests that these factors significantly shape user behavior and intentions, subsequently affecting actual technology usage, with variables like age, gender, and experience playing a moderating role in these influences (Hussain & Papastathopoulos, 2022). UTAUT2 is frequently employed to evaluate technology adoption scenarios, including the use of FinTech services, mobile applications, and other digital systems, as demonstrated in studies by Alalwan, Dwivedi, and Rana (2017). The application of the UTAUT2 model in this research is particularly relevant for delving into the determinants influencing the effective use of FinTech services.

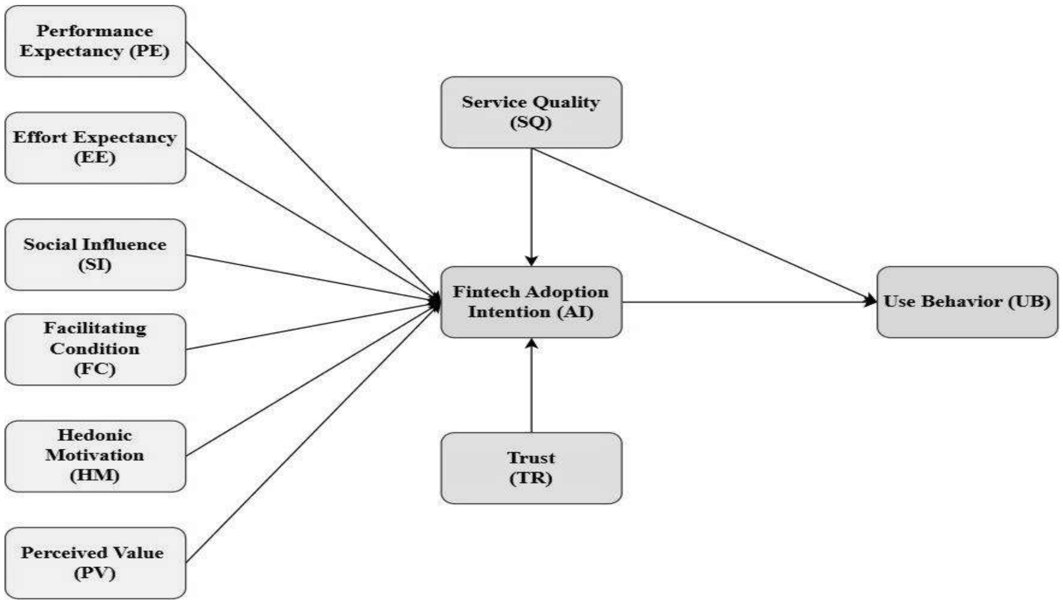

Figure 1: Conceptual Framework of Fintech Adoption Intention

2.1. "Performance Expectancy

Performance expectation (PE) refers to a user's belief in the extent to which a specific technology or system will improve their capacity to complete activities or achieve goals (Venkatesh et al. 2012). It essentially assesses consumers' expectations that technology would improve their productivity by simplifying or streamlining their jobs (De Blanes Sebastián et al. 2023; Martinez and McAndrews 2023). Users are more likely to acquire and use technologies that they believe would improve their productivity or performance (Bajunaied et al. 2023). Ensuring that user experiences meet these performance requirements is crucial for widespread acceptance and use of digital financial services (Basri et al., 2022). Users are more likely to use digital financial services if they consider them to simplify transactions, provide convenience, and improve financial management (Arner et al. 2020; Nawayseh 2020; Senyo and Osabutey 2020). These studies demonstrate a substantial relationship between performance expectancy and technology adoption. Thus, we propose the following hypothesis:

H_1. Performance expectancy positively influences users' fintech adoption intention."

2.2. Effort Expectancy

Effort Expectancy (EE) assesses how easy consumers find understanding and controlling technology (Bajunaied et al. 2023; Venkatesh et al. 2012). The design of user interfaces, the technology's usability, the difficulty of activities required, and the general ease of contact with the system all have an impact on effort expectation. Expected effort has a big impact on consumers' intents to utilize mobile money services. Similarly, an investigation on e-banking in Spain reveals customers likeliness to accept FinTech services because of the easy utilization of these technologies for financial transactions. Thus the following hypothesis can be stated;

H_2. Effort expectancy positively influences users' fintech adoption intention.

2.3. Social Influence

The impact of social influence (SI) is magnified when people understand that significant personalities or groups in their social circles support a technology and push for its adoption (Chen et al, 2022;Venkatesh et al., 2012). A study on FinTech adoption in Spain found that peer recommendations and endorsements had a substantial impact on individuals' decisions to utilize FinTech services (De Blanes et al.,2023). Similarly, testimonials and social media discussions help users grasp the value and reliability of mobile payment systems. The following hypothesis is proposed:

H_3. Social impact has a substantial beneficial effect on users' intentions to adopt fintech.

2.4. Hedonic Motivation

The pleasure or happiness people derive from utilizing technology is known as hedonic motivation (HM) (Dzandu et al. 2022). This idea concedes that individuals are motivated by hedonistic features of technology, including enjoyment, amusement, or social connection, in addition to pragmatic or utilitarian reasons (George and Sunny 2020, 2022). It emphasizes how powerful a tool for influencing user behavior is the perception of pleasure and fulfillment from using technology. According to a research by Yang et al. (2023), gamified features increase the hedonic value of applications and have a beneficial impact on users' intents to use them. Even if their main goal is investing, users who find stock trading applications interesting and pleasurable are more likely to use them (Lee et al. 2022). The significance of pleasure and happiness in propelling the uptake of technological services is shown by these studies. Based on this understanding, the study presents the following hypothesis:

H_4. Hedonic motivation positively impacts users' fintech adoption intention.

2.5. Price Value

Price value (PV), the ratio of the monetary expenses incurred to the perceived advantages of utilizing FinTech technologies. . A favorable price value occurs when the advantages users perceive from a technology significantly outweigh the monetary expenses, thereby strongly influencing their adoption decisions (Venkatesh et al. 2012). Perceived cost reductions, such as lower fees compared to traditional banking, had a favorable influence on consumers' intentions to utilize mobile banking services, according to a study on customer preparedness for FinTech in Bangladesh. Similarly, the affordability of digital payment apps emerged as a crucial factor driving their adoption, particularly in cost-sensitive regions (Carè et al. 2023). Additionally, the perception of lower fees and cost savings influenced decisions to adopt robo-advisory services (Back et al. 2023). Therefore, the following hypothesis can be derived

H_5. Price value positively affects users' fintech adoption intention.

2.6. Facilitating Conditions

The availability of infrastructure, support networks, and resources required for people to utilize a given technology efficiently is referred to as a "facilitating condition" (FC). According to Asif et al. (2023), in order to effectively utilize FinTech services, people need to have access to a mobile device, have a service subscription with a telecoms provider, and be adept in using their mobile devices. These enabling factors can greatly increase interest in and promote the uptake of FinTech services (Aduba et al., 2023). According to research by Bajunaied et al. (2023), consumers' faith in and use of FinTech products are directly impacted by their ability to receive technical help. Furthermore, initiatives to promote digital literacy and training programs are essential for encouraging the use of FinTech (Ong et al. 2023). Drawing from this literature, the study proposes the following hypothesis:

H_6. Facilitating conditions significantly positively affect users' fintech adoption intention.

2.7. Fintech Adoption Intention

Fintech adoption intention (AI) pertains to persons inclination and determination to practice FinTech services, whereas actual utilization is the concrete expression of this behavior (Venkatesh et al., 2012). This idea is derived from the theory of planned behavior (Ajzen 1992), which signals a behavior's intent to be engaged in is a strong indicator of when it will be carried out. Research has confirmed the predictive power of fintech adoption intention with regard to the actual use of technology, including that conducted by Venkatesh et al. (2003) using the UTAUT model. The ambition to adopt fintech is seen to come before using fintech services in practice. People are more likely to demonstrate this in their usage behavior when they have a strong goal to interact with technology (Ajzen 1991). The aim of adopting fintech acts as a mediator between consumers' real FinTech service usage behavior and their attitudes, perceptions, and outside influences. In light of the above discussion, following hypothesis is derived:

H_7. Fintech adoption intention positively influences users' use behavior in FinTech services.

2.8. Trust:

Trust (TR) is the confidence and assurance that clients have in the unwavering quality, security, and integrity of FinTech stages and suppliers. Customers that have faith in FinTech vendors will inevitably express a desire to utilize their services. A concentrate by Bongomin and Ntayi (2019) on portable cash reception pinpointed trust as a vital component foreseeing the utilization conduct of FinTech administrations. Clients who are sure that their monetary data is secure and their protection is maintained are more disposed to think about utilizing FinTech stages (Chauhan 2015). FinTech suppliers that participate in clear and straightforward correspondence with respect to their safety efforts, information the board, and security arrangements are probably going to improve trust, in this manner supporting the use of their administrations (Kilani et al. 2023). Moreover, clients habitually depend on the encounters of their companions to decide reliability. Positive surveys, high evaluations, and solid suggestions can significantly affect trust, which thus impacts purchasers' tendencies to embrace and effectively use FinTech administrations. Laying out and holding trust is basic for FinTech suppliers hoping to increment take-up and long-haul commitment. Based on these insights, this study proposes the following hypotheses:
H_8. Trust positively affects users' intention to apply FinTech services.

2.9. Service Quality:

The service quality (SQ) of Fintech plays a vital role in its adoption by influencing trust, convenience, transparency, and user satisfaction. Trust and reliability are essential for users to feel confident in Fintech platforms. Features like robust fraud detection and reliable functionality reassure users about the security of their funds, while disruptions or errors undermine trust and deter adoption. Fintech's appeal also lies in its convenience and ease of use. High-quality platforms ensure users can complete tasks quickly and intuitively, such as making payments or applying for loans (Venkatesh et al, 2012). User-friendly apps attract customers, while poor design or slow response times discourage them. Similarly, effective customer support reduces barriers, addressing technical concerns through real-time assistance and fostering confidence. Customization and personalization further drive adoption by delivering tailored services like expense tracking or investment advice, enhancing user satisfaction and loyalty (Frederiks et al, 2022). Additionally, transparency in fees and terms builds trust, reducing hesitation and encouraging broader adoption. High-quality services also ensure speed and efficiency, meeting modern user expectations with fast transactions and real-time updates. Finally, security and compliance protect users' data, while adaptability to diverse needs expands Fintech's reach in underserved markets. In summary, high service quality fosters trust, convenience, and confidence, ensuring user satisfaction and driving Fintech adoption. Therefore, we can state the following hypothesis,

H9: Service Quality significantly influence the adoption intention of Fintech.

H10: Service Quality significantly influence the use behavior of Fintech.

3. Research Methodology:

3.1 Sampling and Target Population

Generation Y, or Millennials, states to individuals born between 1981 and 1996, following Generation X and preceding Generation Z. They are highly tech-savvy, having grown up during the rise of the internet, mobile phones, and social media. Millennials are often well-educated, prioritizing personal and professional growth. They value meaningful work, work-life balance, and flexible, collaborative environments. Socially conscious, they care about issues like climate change and social justice, often aligning purchases with ethical values. As digital natives, they heavily use online platforms for communication, shopping, and entertainment, preferring experiences over possessions and expecting personalized, seamless interactions.

When selecting students from various higher education institutions in Bangladesh, the researchers utilized a judgmental sampling approach. The participants were from 'Y generation'. The selection process was designed to ensure equal participation opportunities for all students. An electronic survey was distributed via email and WhatsApp groups, facilitated by the respective institutions. From the initial 405 completed responses, 349 were deemed suitable for detailed analysis due to data quality issues and significant deviations. This resulted in an actual response rate of 86%. Respondents profile are as follows: 52.14% were male and 47.86% were female. Regarding age distribution, 37.24% were between 18 and 22 years, 37.53% between 22 and 26 years, and 25.23% were between 26 and 30 years old. In terms of education, 52.72% were professionals, 21.48% had earned bachelor's degrees, and 25.80% had earned postgraduate degrees.

3.2 Questionnaires:

This research has selected respondents those who have relevant knowledge and open to respond. The questionnaire was separated into two parts: A and B. Part A includes demographic information such as age, gender, educational qualifications, phone types, employment, and dwelling area/district, among other things. Part B asks questions on the many constructs offered in the study model, as stated in Table 4.

4. Results:

We carried out several statistical tests to evaluate multivariate assumptions. First, the mean is determined, and the lowest and maximum standard deviations are displayed in **Table 1**. The dataset's normality was then ascertained using the Kolmogorov-Smirnov test. As shown in **Table 2,** the p-values for this test were all below 0.05, indicating that the dataset does not follow a normal distribution.

Table 1: Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
PE	349	3.5319	1.84798	1.00	19.17
EE	349	3.6152	3.02143	1.00	27.50
HM	349	2.7778	1.09738	1.00	5.00
FC	349	3.5567	2.26274	1.00	27.50
SI	349	3.1348	1.11704	1.00	5.00
PV	349	4.5839	3.87240	1.00	36.00
AI	349	4.0804	8.54947	1.00	99.00
US	349	2.8564	1.12925	1.00	5.00
TR	349	4.1277	0.90367	1.00	5.00
SQ	349	3.6879	2.51392	1.00	19.83

Table 2: Kolmogorove-Simrov Test

		PE	EE	HM	FC	SI	PV	AI	US	TR	SQ
N		349	349	349	349	349	349	349	349	349	349
Normal Parameters[a,b]	Mean	3.53	3.62	2.78	3.56	3.13	4.58	4.08	2.86	4.13	3.69
	Std.	1.85	3.02	1.10	2.26	1.12	3.87	8.55	1.13	0.90	2.51
Most Extreme Differences	Absolute	.224	.309	.183	.255	.133	.443	.443	.097	.196	.280
	Positive	.224	.309	.157	.255	.061	.443	.443	.095	.167	.280
	Negative	.146	.204	.183	.176	.133	.277	.359	.097	.196	.202
Test Statistic		.224	.309	.183	.255	.133	.443	.443	.097	.196	.280
Asymp. Sig. (2-tailed)		.000[c]	.000[c]	.000[c]	.000[c]	.000[c]	.000[c]	.000[c]	.003[c]	.000[c]	.000[c]
a. Normal Distribution.											
b. Lilliefors Significance Correction.											

4.1 Model Fitness:

After assessing the multivariate assumptions, the model fitness testing was initiated. The following data table provides the lists of various reliability and validity statistics for different constructs or variables (e.g., BI, EE, FC). Here's a breakdown of what each column represents and the interpretation of these values.

Table 3: Model Fitness of Fintech Adoption

Variables	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
UB	0.880	0.880	0.807
EE	0.865	0.869	0.711
FC	0.853	0.854	0.694
HM	0.788	0.737	0.618
PE	0.824	0.843	0.651
PV	0.830	0.837	0.746
AI	0.851	0.854	0.771
SI	0.768	0.768	0.683
SQ	0.777	0.783	0.692
TR	0.775	0.791	0.688

4.2 Interpretations of the Model Fitness:

The values above 0.7 of Cronbach's alpha indicating high reliability and good correlation among items. These measures are considered more robust than Cronbach's Alpha as they account for different indicator loadings. Average Variance Extracted (AVE) with values above 0.5 indicating that the construct explains more than half of the variance, suggesting adequate convergent validity. Constructs such as UB, EE, FC, HM, PE, PV, AI, SI, SQ, and TR generally demonstrate high reliability values, along with strong validity (AVE values above 0.5). These indicators affirm that the constructs are robust measures of their respective domains.

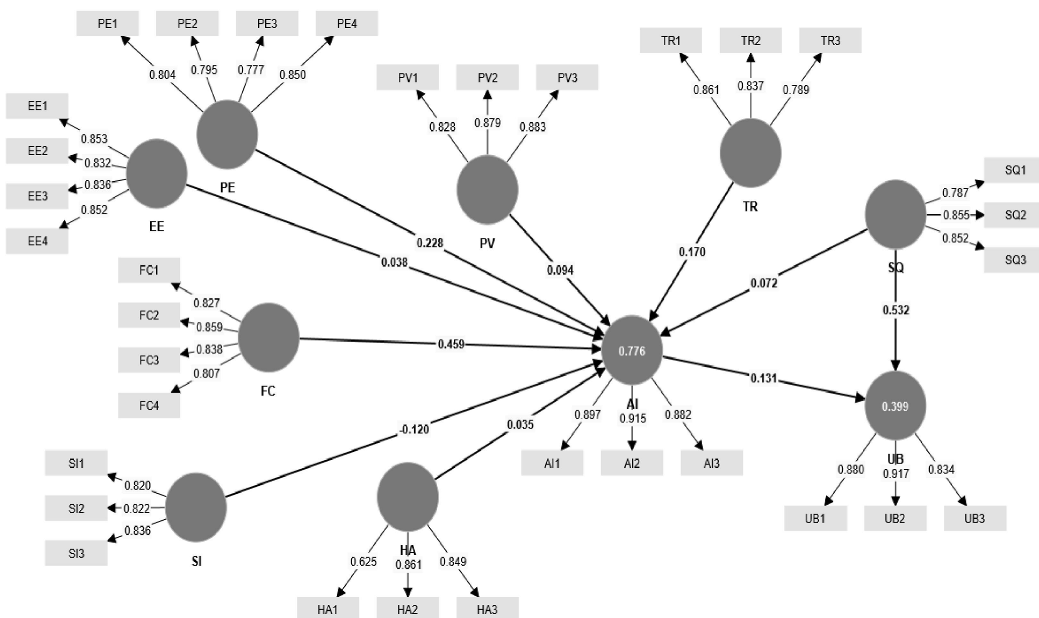

Figure 2: Measurement Model

4.3 Discriminant Validity:

Values close to or below 0.85 indicate good discriminant validity, suggesting constructs are distinct. Most values in your matrix fall below this threshold, implying minimal overlap. Values above 0.85, such as UB and PE (0.883) and TR and UB (0.872), suggest potential overlap and may require further investigation. Lower values, like UB and AI (0.584) and UB and SI (0.544), strongly support discriminant validity. Moderate values around 0.7-0.8, such as EE and FC (0.862) and TR and PV (0.872), suggest acceptable discriminant validity but require careful interpretation. Overall, HTMT results mostly support good discriminant validity, with a few exceptions needing further validation (**Table 4**).

Table 4: Heterotrait-monotrait ratio (HTMT) - Matrix

Variables	UB	EE	FC	HM	PE	PV	AI	SI	SQ	TR
UB										
EE	0.797									
FC	0.604	0.862								
HM	0.702	0.746	0.779							
PE	0.883	0.790	0.775	0.752						
PV	0.759	0.654	0.650	0.876	0.732					
AI	0.584	0.639	0.575	0.782	0.875	0.704				
SI	0.544	0.600	0.639	0.784	0.568	0.687	0.573			
SQ	0.749	0.799	0.764	0.771	0.551	0.779	0.770	0.661		
TR	0.772	0.729	0.755	0.721	0.546	0.872	0.824	0.717	0.789	

4.4 Structural Model:

The bootstrapping approach was utilized to examine the claimed association between the dependent and independent variables using the path coefficient (β) and t test at a significance threshold of 0.05 ($p < 0.05$). Based on the provided data, we can conclude that several factors significantly influence Artificial Intelligence (AI) and User Behavior (UB). The relationships of AI with UB, Facilitating Conditions (FC), Performance Expectancy (PE), Price Value (PV), Social Influence (SI), and Trust (TR) are all statistically significant. Specifically, Facilitating Conditions, Performance Expectancy, and Trust have strong positive impacts on AI, while Social Influence has a negative impact. Additionally, AI itself and Service Quality (SQ) significantly influence User Behavior, with Service Quality showing a notably strong positive impact.

Table 5: Hypothesis Testing

Hypothesis	Path	Beta Value *(β)*	Sample mean (M)	(STDEV)	T statistics	P values
H1	**AI -> UB**	0.131	0.130	0.056	2.332	0.020
H2	**EE -> BI**	0.038	0.037	0.046	0.838	0.402
H3	**FC -> BI**	0.459	0.459	0.065	7.081	0.000
H4	**HM -> BI**	0.035	0.035	0.051	0.690	0.490
H5	**PE -> BI**	0.228	0.226	0.054	4.238	0.000
H6	**PV -> BI**	0.094	0.094	0.043	2.171	0.030
H7	**SI -> BI**	-0.120	-0.114	0.041	2.887	0.004
H8	**TR -> BI**	0.170	0.171	0.044	3.912	0.000
H9	**SQ -> RC**	0.532	0.532	0.056	9.558	0.000
H10	**SQ -> BI**	0.072	0.070	0.050	1.425	0.154

Conversely, Effort Expectancy (EE), Hedonic Motivation (HA), and Service Quality (SQ) do not significantly influence AI. The non-significant relationships indicate that these factors do not have a measurable impact on AI in this dataset. The overall findings highlight the importance of Facilitating Conditions, Performance Expectancy, Price Value, Social Influence, and Trust in shaping AI outcomes, as well as the critical role of AI and Service Quality in affecting User Behavior. Further analysis or visualizations could provide additional insights into these relationships.

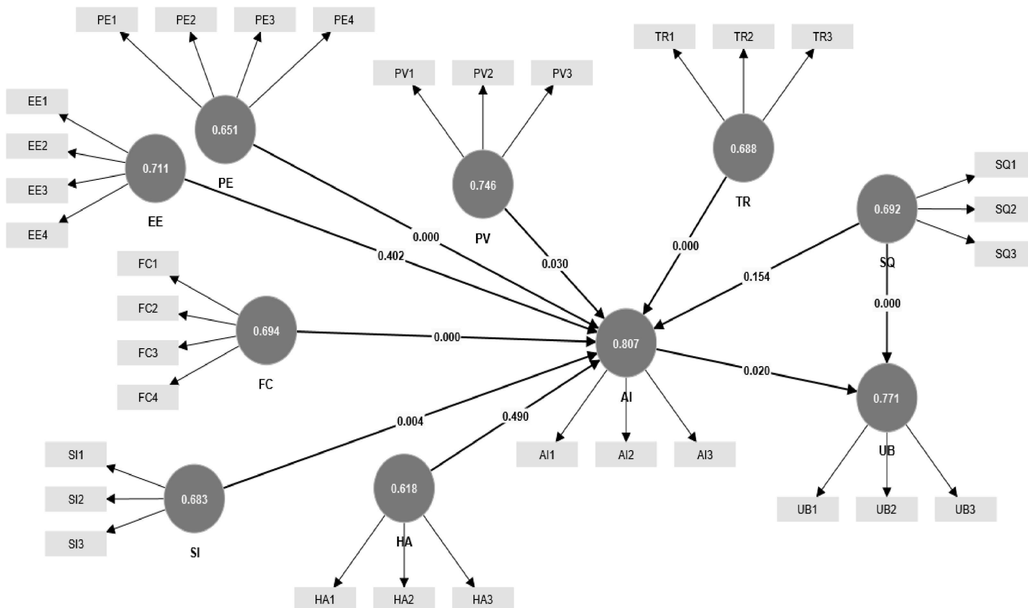

Figure 1: Path Analysis

5. Discussion and Findings:

The study underscore the critical importance of several key factors in influencing both FinTech adoption intention (AI) and user behavior within the FinTech sector. Performance Expectancy (PE), Facilitating Conditions (FC), and Trust (TR) emerged as significant positive influencers on AI. This implies that consumers are more likely to utilize fintech technologies when they believe these technologies will enhance their performance, are supported by adequate resources and infrastructure, and are trustworthy. The strong positive impact of these factors highlights the need for FinTech companies to focus on building reliable, user-friendly, and supportive environments that foster trust and enhance perceived performance benefits. Interestingly, Social Influence (SI) showed a negative impact on AI, which could indicate that users might be skeptical of peer recommendations or overly cautious about new technologies despite social endorsements. These above findings show similarity with the existing researches of FinTech adoption (Pavlo et.al 2006, Zeithaml et.al 2018, Venkatesh et. al 2016).

On the other hand, Effort Expectancy (EE) and Hedonic Motivation (HM) did not show a significant influence on AI, indicating that ease of use and enjoyment might not be as crucial for users when deciding to adopt FinTech technologies. This could be due to the functional and goal-oriented nature of financial technologies where practicality and utility outweigh the pleasure of use. Additionally, the analysis revealed that Service Quality (SQ) significantly impacts User Behavior (UB), emphasizing that high-quality service can lead to increased user engagement and satisfaction. These insights suggest that while foundational elements such as trust, performance benefits, and facilitating conditions are vital for initial FinTech adoption, maintaining high service quality is key to sustaining user engagement. Overall, these findings provide valuable guidance for FinTech companies aiming to enhance AI adoption and user satisfaction by focusing on critical factors that influence user perceptions and behaviors.

In sum, the study highlights the critical importance of Performance Expectancy (PE), Facilitating Conditions (FC), and Trust (TR) as significant positive influencers of Fintech Adoption Intention (AI). Interestingly, Social Influence (SI) negatively impacts AI, possibly reflecting users' skepticism about peer recommendations. Effort Expectancy (EE) and Hedonic Motivation (HM) are not significant predictors, suggesting that practical utility outweighs ease of use and enjoyment. Practical implications for FinTech providers include prioritizing trust-building, robust infrastructure, and high service quality to sustain user engagement.

5.1 Theoretical Contributions

The study adds to the theoretical understanding of FinTech by expanding the UTAUT2 model to the setting of Bangladesh. By include new dimensions like as information quality and willingness to pay for services, the study gives a more thorough framework for understanding the elements impacting FinTech adoption intention. The findings underscore the relevance of traditional UTAUT2 constructs like Performance Expectancy, Facilitating Conditions, and Trust, while also highlighting the nuanced role of Social Influence, which contrasts with its typical positive impact in other contexts. This study further contributes to the literature by exploring the insignificant impact of Effort Expectancy and Hedonic Motivation on the intention to adopt FinTech, indicating that practical and utilitarian factors might be more influential than ease of use and enjoyment in the realm of financial technologies. This insight challenges existing assumptions in technology adoption models and calls for further exploration into context-specific factors that may moderate these relationships. Overall, the study enhances the theoretical framework of FinTech adoption by integrating context-specific variables and providing empirical evidence from a developing country perspective.

5.2 Practical Contributions

The significant positive influence of Performance Expectancy (PE), Facilitating Conditions (FC), and Trust (TR) on FinTech adoption intention (AI) suggests that companies should prioritize the development of technologies that demonstrably enhance user performance and simplify tasks. Ensuring robust and reliable infrastructure, along with clear communication of security measures, can build user trust and encourage adoption. Such as, platforms like PayPal have built trust through robust security measures, such as encryption and fraud protection, which are clearly communicated to users, thereby encouraging broader adoption. These findings further emphasize the significance of providing sufficient resources and support mechanisms to ensure the seamless operation of FinTech apps.

Moreover, the negative impact of Social Influence (SI) on AI indicates that marketing strategies relying solely on peer recommendations or social endorsements may not be effective. Instead, a focus on individual user experiences and the tangible benefits of the technology might be more persuasive. Take, for example, the customer service offered by companies like Revolut or Chime, which are known for their responsive and helpful customer support teams. The significant role of Service Quality (SQ) in influencing User Behavior (UB) emphasizes that high-quality customer service and user support are crucial for maintaining user engagement and satisfaction. FinTech companies should invest in customer service training and infrastructure to ensure a positive user experience that can lead to long-term user retention.

Limitations and Future Research Directions

Notwithstanding, this research has also several limitations. Firstly, the results may have limited generalizability because of the judgmental selection method and the focus on Generation Y students from Bangladeshi higher education institutions. The sample may not fully represent the diverse demographics of the entire Bangladeshi population, including older generations or those not engaged in higher education. This sampling approach could lead to biases in understanding the broader adoption behaviors and preferences towards FinTech services. Secondly, the cross-sectional design of the study restricts the ability to determine causal relationships between the variables. While significant relationships were identified between constructs like Performance Expectancy, Facilitating Conditions, Trust, and FinTech adoption intention, a longitudinal study would provide more robust insights into how these relationships evolve over time. Additionally, the reliance on self-reported data through surveys may introduce common method biases, as responses could be influenced by social desirability or respondents' current mood and context.

Subsequent studies have to think about enlarging the sample to encompass a more varied cross-section of the Bangladeshi populace.
Incorporating participants from diverse age cohorts, educational levels, and geographic regions will augment the applicability of the results and furnish a more comprehensive perspective on FinTech adoption practices in Bangladesh. Likewise, examining different user segments, such as small business owners or rural residents, could uncover unique factors influencing FinTech adoption in these groups. Longitudinal studies are recommended to explore the dynamic nature of FinTech adoption over time. Such studies can provide deeper insights into how user perceptions and behaviors change with continued exposure to and experience with FinTech services. Finally, comparative studies between Bangladesh and other developing countries could highlight cultural and contextual differences in FinTech adoption, offering broader implications for global FinTech strategies and policies.

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