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FINTECH ADOPTION AMONG GENERATION X IN URBAN PUNJAB: A UTAUT-BASED STRUCTURAL EQUATION MODELING APPROACH USING SMARTPLS

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Abstract

Generation X in the Indian paradigm is generally the key earner in the family and helps make essential financial decisions. However, literature on FinTech (financial technology) primarily focuses on Generation Z or Y because they are digital savvy. This study uses UTAUT framework and methodology to examine Generation X FinTech adoption in Punjab, India. It examines the direct effect of all basic UTAUT constructs as independent variables on Behavioural Intention (BI); and also of BI as mediator in the link between independent variables as per UTAUT framework on FinTech actual use behavior. The analysis of 341 Generation X respondents' data using SmartPLS reveals that all proposed independent variables possess a significant positive influence on BI. Further, the results reveal that BI significantly and positively mediates the influence of all proposed independent variables of UTAUT framework on actual FinTech use. This study is unique in its focus on Generation X, a cohort understudied in FinTech adoption research. The research plugs this void, providing insights that can help FinTech developers and policymakers create inclusive, user-friendly digital financial products.

Keywords: *FinTech, Adoption, Behavioral Intention, Generation X, UTAUT, SEM, SmartPLS*

1. INTRODUCTION

FinTech's rapid evolution and integration have transformed the global financial ecosystem in the 21st century as it utilises digital technologies to supply financial products and services, disrupting conventional banking & financial structures (Arner et al., 2016). Digital payments, mobile wallets, crowd based funding, peer-to-peer lending, robo-advisory, crypto-currency trading and blockchain enabled smart contracts are among its services. FinTech has evolved in phases as FinTech 1.0 (1950s–1990s) was infrastructure-driven, including ATMs and electronic stock trading (Puschmann, 2017). The FinTech 2.0 wave (2008–2014) began when companies used cloud computing, big data analytics, and artificial intelligence to fill holes left by established banks after the 2008 financial crisis. Fully digital banking ecosystems, embedded finance, BNPL (Buy Now, Pay Later) models, and improved financial inclusion for underprivileged people characterise FinTech 3.0.

On the global stage, FinTech has witnessed explosive growth in the last decade, with market penetration reaching unprecedented levels. According to PwC's 2022 Global FinTech Report, global FinTech funding exceeded USD 120 billion in 2021, with investments continuing to surge despite market volatility (PwC, 2022). Digital payment platforms, such as PayPal, Stripe, and Square (Block, Inc.), have become ubiquitous, handling trillions of dollars in transactions annually. Furthermore, the global cryptocurrency market has expanded into a trillion-dollar industry, with Bitcoin, Ethereum, and other blockchain-based technologies driving decentralized finance (DeFi). Traditional financial institutions are no longer the sole players in financial services, as FinTech companies have increasingly captured market share in lending, insurance and asset management sectors through innovative business models and improved customer experiences (Arner et al., 2016). The industry increased financial inclusion and changed consumer money management by providing digital financial services to over 60% of the worldwide population in 2021 (World Bank, 2021). Mobile payments and digital banking have grown rapidly in China and Singapore, while FinTech companies have spurred digital lending platforms in Southeast Asia. Open banking and regulatory sandboxes in many countries allow innovators to test new products in a controlled, regulated environment, driving FinTech. Flexible rules let new companies bring change while still keeping consumers and the financial system safe (Zetzsche et al., 2017).

Indian FinTech is a global leader due to its young, tech-savvy population, growing smartphone penetration, and favourable government regulations. The country's FinTech industry has grown tremendously, with over 3,000 startups providing digital payments, lending, insurtech and wealthtech. The RBI (“Reserve Bank of India”) has promoted innovation through regulatory initiatives like the PMJDY “Pradhan Mantri Jan Dhan Yojana”, which aims to provide universal banking services. UPI (“Unified Payments Interface”), which has revolutionised digital transactions in India; and one of the largest real-time payment systems, processing over 10 billion transactions per month in 2023 (RBI, 2023). India's FinTech sector in 2021 was of worth USD 50 billion and predicted to attain USD 150 billion by year 2025. Paytm, PhonePe, Google Pay and Amazon Pay, which allow bill payments and peer-to-peer transfers, have made mobile payments popular in urban and rural areas. Digital wallets, micro-lending and insurance have helped marginalised groups access financial services.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

This section examines the current literature on technology adoption in consonance with UTAUT, emphasising the interconnections among critical variables such as performance expectancy, effort expectancy, social influence and facilitating conditions. Proposed associations will be formulated as hypothesized assumptions for statistical validation based on this review.

UTAUT Framework

The "Unified Theory of Acceptance and Use of Technology (UTAUT) is a comprehensive model for technology adoption across fields. Technology use behaviour can be predicted using the UTAUT framework, which combines vital variables from the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB). Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC) influence Behavioural Intention (BI), which affects Actual Use Behaviour (AU). Performance Expectancy is the extent to which a technology improves job performance, whereas Effort Expectancy is its perceived ease of use". SI signifies providing importance to others' influence on technology usage; and Facilitating Conditions refers to resources that facilitate technology use. In mobile technology and e-commerce research, UTAUT predicts acceptance and use in different cultural and technological environments.

Relationship between PE and BI: Performance Expectancy is how much a person believes a technology will help them do their job better. In FinTech adoption, PE shows how helpful mobile wallets or financial technologies are for financial transactions, saving time and convenience. People are more likely to adopt innovations they think will improve their lives, especially if they offer real benefits (Venkatesh et al., 2003). This perception of greater productivity and efficiency drives technological adoption.

H_1: PE positively influences BI to adopt FinTech services

Relationship between EE and BI: Technology ease of use is called effort expectancy. When technology is simple, customers are more inclined to use it. Users tend to use FinTech services or mobile wallets more likely, if users perceive the technology is intuitive, user-friendly, and easy to grasp (Venkatesh et al., 2003). Technologies that require frequent use must be easy to use to reduce cognitive burden and improve enjoyment.

H_2: EE positively influences BI to adopt FinTech services

Relationship between SI and BI: SI is the extent of others' opinions (like family, friends or coworkers) which affect a person's choice to use a technology (Venkatesh et al., 2003). People are more prone to follow social norms, especially when they see their friends or powerful personalities adopting and recommending FinTech. Social influence makes people follow trends, especially in mobile technology, where peer recommendations and social expectations drive technology diffusion.

H_3: SI positively influences BI to adopt FinTech services

Relationship between FC and BI: In financial services, this includes stable internet connections, appropriate mobile devices and mobile wallet integration with merchants or service providers. People are more inclined to adopt technology if they think the environment supports it (Venkatesh et al., 2003). Greater access to resources and support systems increases FinTech adoption.

H_4: FC positively influences BI to adopt FinTech services

Relationship between BI and AU: Behavioral Intention is a significant predictor of actual technology usage behavior. According to the Theory of Planned Behavior, the more an individual intends to perform a behavior, the more likely they are to engage in it (Ajzen, 1991). In the case of mobile wallets, Behavioral Intention reflects the decision or plan to use the technology. When users have a forceful intent to adopt FinTech services, they are then further expected to follow it through and use them in real-world scenarios, provided that there are no significant barriers.

H_5: BI positively influences AU to adopt FinTech services

Relationship among PE, BI and AU: Performance Expectancy not only directly influences Behavioral Intention but can also indirectly influence Actual Use Behavior through BI as a mediator. If individuals believe that using FinTech services will improve their financial transactions or provide better financial management, their intention to adopt the technology will be stronger. This intention will eventually translate into actual usage if the perceived performance gains are realized (Venkatesh et al., 2003). Thus, Performance Expectancy serves as a critical factor both in shaping adoption intention and in promoting sustained use.

H_6: BI positively mediates the relationship between PE and AU to adopt FinTech services

Relationship among EE, BI and AU: Effort Expectancy affects both BI and AU to embrace a technology. When technology is easy to use, users use it more. If people have a smooth, frictionless experience, they will stick with it (Venkatesh et al., 2003). Thus, FinTech service easy usability and user-friendliness can boost intention and retention.

H_7: BI positively mediates the relationship between EE and AU to adopt FinTech services

Relationship among SI, BI and AU: People are more likely to use FinTech services like mobile wallets if they feel social pressure from their social networks or society. In tech adoption, peer recommendations and social norms drive usage (Venkatesh et al., 2003). Thus, Social Influence possesses the credence to influence the FinTech service use behaviour through its effect on intention.

H_8: BI positively mediates the relationship between SI and AU to adopt FinTech services

Relationship among FC, BI and AU: Supportive infrastructure can affect Behavioural Intention and Actual Use Behaviour. If people think the technological, organisational and societal conditions promote FinTech or mobile wallet use, they are more likely to accept it. If resources like internet connection or cellphone compatibility are accessible, this purpose may lead to use.

H_9: BI positively mediates the relationship between FC and AU to adopt FinTech services

FinTech Adoption: Present Outlook

Sharma et al. (2023) utilised the UTAUT model to explore the growing use of FinTech services among Indian adults, emphasising characteristics such as PE, EE and SI. Amnas et al. (2023) improved the

UTAUT2 model by uniting a Trust Theoretic Model, outlining the indispensable influence of trust on consumers' decisions on FinTech adoption. Chan et al. (2022) investigated the influence of the open banking framework on customers' attitudes and their keenness to embrace FinTech services, reflecting that transparency and trust are vital for adoption. Shaikh and Amin (2024) researched to determine the effect of consumer innovativeness on FinTech adoption in Pakistan, exhibiting that extra innovative customers are predisposed to embrace new financial technology, consitent with research inferences of Sharma et al. (2023). Bashir and Muhammad (2023) examined the influence of mobile financial services on financial inclusion, utilising SEM to determine the primary factors influencing adoption in developing economies, highlighting the contribution of these services to overarching financial inclusion objectives.

Unexplored FinTech Potential of Generation X

Research in FinTech has mainly concentrated on tech-savvy Millennials and Gen Z, yet Generation X with their higher income and increasing faith on digital convenience remains an underexplored demographic cohort (Chan et al., 2022). Further, studies indicates that trust and perceived utility exhibit an important role in technology adoption among middle-aged consumers in Asia, although FinTech firms often prioritize younger demographics (Amnas et al., 2023). In India, despite initiatives such as Digital India and UPI, the unique financial behaviors and needs of Generation X remain mostly unaddressed (Sharma et al., 2023). As mobile financial services continue to expand under the broader umbrella of financial inclusion, offering personalized solutions to this cohort is increasingly vital (Bashir & Muhammad, 2023). Trust deficits, steeper learning curves and loyalty to traditional banking contribute to slower adoption in this group (NITI Aayog, 2021). Moreso, Generation X represent a financially empowered but often overlooked FinTech consumer segment. Understanding generational adoption gaps and digital behavioral inertia may offer valuable insights for designing inclusive FinTech strategies and provisions. This study specifically explores Generation X in urban Punjab, identifying them as a population with untapped potential for FinTech expansion across both age and cultural dimensions.

3. RESEARCH METHODOLOGY

The present research is a descriptive, causal and cross-sectional endeavour on Generation X consumers in urban Punjab. The studied variables of UTAUT are examined in relation to FinTech application usage intention and behaviour. Primarily, a quantitative research approach collects and analyses numerical data for rigorous statistical analysis. The study employs SmartPLS 4.0 for Structural Equation Modelling (SEM) to investigate the postulated structural links as hypothesized among variables. All items utilised a 7-point Likert scale for stronger internal consistency, improving data reliability and model variance. This study targets Generation X respondents aged 45–60 in the state of Punjab, India. Stratified random sampling was initially utilised to select one district from each of the historically evident strata of Punjab and thereon purposive sampling was used to distribute 125 questionnaires in each of the selected district i.e. Ludhiana, Amritsar and Jalandhar. The final sample consists of 341 respondents which represent 121 respondents (35.5%) from Ludhiana, 106 respondents (31.1%) from Amritsar 114 respondents (33.4%) from Jalandhar. This sample size meets Hair et al. (2017) PLS-SEM recommendations, ensuring statistical power and generalisability.

Table 1: Measurement of Constructs and Their Sources

Construct Abbreviation	Source(s) Referred
PE; EE; SI; FC; BI; AU	Venkatesh et al. (2003)
FC	Alalwan et al. (2017)

5. STATISTICAL RESULTS AND DISCUSSION

Data robustness was assured via reliability, validity, and SmartPLS 4.0 path analysis. To test hypotheses and investigate direct and indirect effects, bootstrapping was used.

Table 2: Construct Reliability and Convergent Validity Measures

Construct Abbreviation	Cronbach's alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
AU	0.747	0.753	0.854	0.662
BI	0.896	0.897	0.935	0.828
EE	0.793	0.811	0.877	0.704
FC	0.728	0.734	0.843	0.642
PE	0.846	0.859	0.907	0.765
SC	0.795	0.820	0.878	0.706

As detailed in the aforesaid table, all six conceptions have good internal consistency and convergent validity. Cronbach alpha value ranges from 0.728 to 0.896, all above 0.70, indicating strong internal reliability (Nunnally & Bernstein, 1994). Composite reliability (rho_c) values, which exceed the suggested cutoff of 0.70 and AVE values, which exceed 0.50, indicated that each construct's indicators explain a significant portion of variance (Hair et al., 2021). These results validate the measurement model's robustness and applicability for structural model analysis by showing that the constructs are reliable and valid.

Table 3: Fornell-Larcker Criterion for Discriminant Validity

	AU	BI	EE	FC	PE	SI
AU	0.813					
BI	0.552	0.910				
EE	0.582	0.645	0.839			
FC	0.507	0.395	0.438	0.802		
PE	0.474	0.564	0.615	0.367	0.875	
SI	0.795	0.404	0.235	0.073	0.215	0.840

The Fornell-Larcker criterion for discriminant validity in structural equation modelling assures that a construct is more strongly associated to its own indicators than to those of other constructs (Fornell & Larcker, 1981). The diagonal AVE square roots exceed inter-construct correlations. The square root of AVE for BI is 0.910, which exceeds its association with EE (0.645) and PE (0.564), confirming discriminant validity. AU's diagonal value of 0.813 exceeds its maximum inter-construct correlation (0.582 with EE), confirming each construct's uniqueness. These findings demonstrate that the model meets literature-recommended discriminant validity standards (Hair et al., 2021; Henseler et al., 2015), bolstering the measurement model's legitimacy.

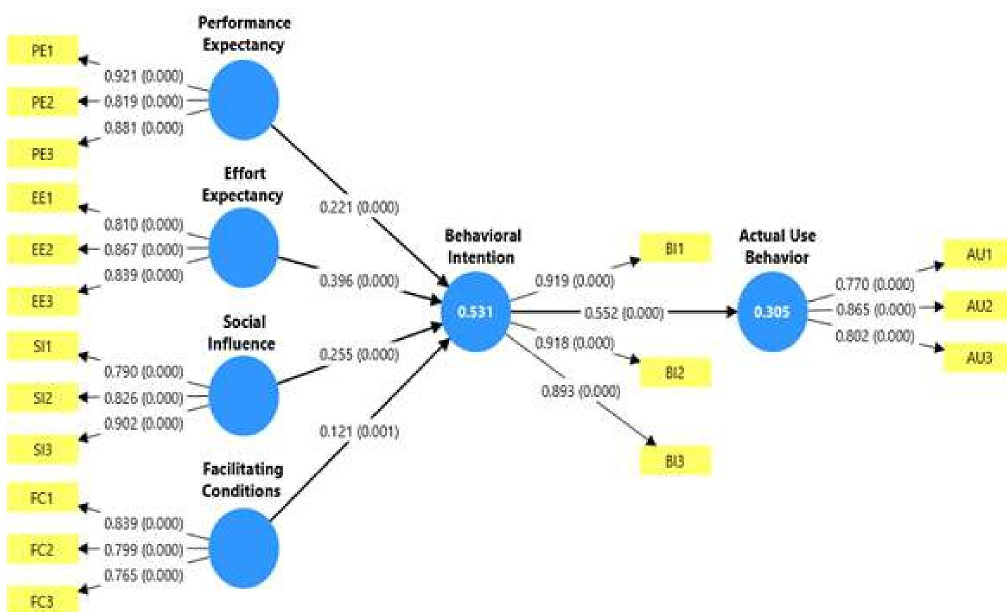

Figure 1: Bootstrapping Results of the Structural Model

Bootstrapping was used to test direct and indirect effects between constructs, validating hypotheses. All item factor loadings above 0.70, meeting Hair et al. (2017) requirements for indication dependability.

Table 4: Direct Effects

Direct Effect	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
EE → BI	0.396	0.393	0.031	12.730	0.000
FC → BI	0.121	0.121	0.035	3.451	0.001
PE → BI	0.221	0.223	0.051	4.304	0.000
SI → BI	0.255	0.254	0.049	5.194	0.000
BI → AU	0.552	0..554	0.030	18.552	0.000

Effort Expectancy (EE) had the greatest impact on BI ($\beta = 0.396$, $t = 12.730$, $p < 0.001$), indicating that users are more inclined to use FinTech services that are easy to use. Baptista and Oliveira (2015), another UTAUT-based FinTech study, revealed EE to be a major predictor of mobile banking adoption in Portugal. Facilitating Conditions (FC) significantly impacted BI ($\beta = 0.121$, $t = 3.451$, $p < 0.01$), highlighting the importance of resources and infrastructure in FinTech (e.g., technical support, app tutorials, secure mobile networks). Kaur et al. (2020) found that internet connectivity, mobile devices and customer support services drove mobile wallet use in India. FC is especially influential in emerging nations, where digital literacy and access gaps remain and making enabling infrastructure essential for FinTech's consistent upward progression. Performance Expectancy (PE) ($\beta = 0.221$, $t = 4.304$, $p < 0.001$) indicates that customers are drawn to FinTech platforms for tangible benefits such speedier transactions, lower expenses and improved financial management. Alalwan et al. (2017) and Dwivedi et al. (2021) found that PE consistently influences user intention in mobile banking and digital lending, especially among business users and digitally savvy millennials who want convenience and functionality from FinTech tools. BI was strongly influenced by social influence (SI) ($\beta = 0.255$, $t = 5.194$, $p < 0.001$), suggesting that peer, family or influencer opinions can influence individuals' desire to adopt FinTech platforms. Yu (2012) and Cruz et al. (2010) found SI to be especially important in FinTech uptake in collectivist cultures where social endorsement and community trends drive behavioural changes. The substantial correlation between BI and AU ($\beta = 0.552$, $p = 0.000$) indicates that user intention strongly impacts usage behaviour. This supports previous FinTech studies that found a strong correlation between intention and digital financial service uptake and usage (Oliveira et al., 2016; Kaur et al., 2020; Sharma et al., 2023).

Table 5: Mediating Effects

Mediating Effect (Mediating Role of BI	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
EE → BI → AU	0.219	0.218	0.022	9.870	0.001
FC → BI → AU	0.067	0.067	0.020	3.359	0.000
PE → BI → AU	0.122	0.124	0.031	3.964	0.000
SI → BI → AU	0.141	0.140	0.026	5.336	0.000

The mediation study shows that Behavioural Intention (BI) is crucial to bridging UTAUT components' impact on FinTech adoption's Actual Use Behaviour (AUB). The strong and significant correlation between Effort Expectancy (EE) and AUB through BI ($\beta = 0.219$, $t = 9.870$, $p < 0.01$) suggests that users who perceive FinTech platforms as easy to use are more likely to form strong behavioural intentions that lead to actual usage. Baptista and Oliveira (2015) found that EE indirectly drives mobile banking in Portugal through intention. The indirect impact of Facilitating Conditions (FC) on AUB through BI was significant ($\beta = 0.067$, $t = 3.359$, $p < 0.01$), albeit moderate. Internet connectivity, help centres and app tutorials may not directly impose usage, but they increase intention, which promotes adoption. Performance Expectancy (PE) shows a substantial BI-mediated influence ($\beta = 0.122$, $t = 3.964$, $p < 0.01$), showing that perceived FinTech service usefulness (e.g. efficiency, financial transparency, cost-savings) increases intention and promotes actual use. Alalwan et al. (2017) found that performance-oriented perks such transaction speed and 24/7 availability of mobile banking services strongly influence Middle Eastern customers' intention and usage behaviour. The study indicated that Social Influence (SI) indirectly affects AUB through BI ($\beta = 0.141$, $t = 5.336$, $p < 0.01$), highlighting the influence of peer opinions, family endorsements and organisational directives on technological acceptance. Yu (2012) and Cruz et al. (2010) found that SI increases behavioural intention, a good predictor of FinTech participation, in collectivist societies and tight-knit professional communities.

5. IMPLICATIONS

For consumers: FinTech platform acceptance depends on simplicity of use, perceived utility and social impact. When FinTech systems are easy to use, consumers are more inclined to use them. Therefore, FinTech companies should prioritise user-friendly interfaces and remove barriers to a seamless user experience, such as cumbersome sign-up processes or unclear features. Customers are also motivated by the assumption that FinTech platforms may improve their financial lives, whether through speedier transactions, better financial management or enhanced security. FinTech providers must properly express their value and efficiency, especially for first-time users. Facilitating factors like reliable internet and customer support boost consumer confidence. As digital financial services can be scary, strong customer service and technical support are crucial for consumers with challenges. Since customers trust peers, family and online groups, social influence is also important. Positive user experiences, social media presence and word-of-mouth marketing help financial services build consumer trust and acceptance.

For Businesses: The findings highlight many ways to boost consumer uptake and engagement. First, the substantial correlation between effort expectancy and behavioural intention suggests that organisations should simplify their platforms to attract consumers. FinTech companies with clear instructions and user-friendly designs would likely have greater adoption rates. User experience design and interface testing are vital for smooth interaction. Businesses should provide sufficient infrastructure and assistance for users to facilitate circumstances. This could include 24/7 customer assistance, reliable online banking and educational tools to help users maximise the platform's benefits. Businesses should emphasise their services' visible benefits because performance expectancy, belief that a system will simplify financial tasks, is key to modelling behavioural intention. Providing efficiency, security and simplicity will boost consumers' opinions of the platform's value.

6. CONCLUSION

This study examined FinTech adoption based on the UTAUT's effort expectancy, enabling conditions, performance expectancy and social influence. The results show that consumers' behaviour is influenced by perceived ease of use, resources and assistance and technology performance. Social impact, including peer and organisational opinions, strengthens FinTech adoption intentions. These findings emphasise the role of individual and environmental factors in FinTech adoption. The study also shows that behavioural intention mediates these characteristics and actual use behaviour. The results indicate that consumers' intents to adopt FinTech are positively influenced by its simplicity of use, work performance potential and support. Intentions strongly predict usage behaviour and this mediation endeavour emphasises the importance of user attitudes and external influences in FinTech integration into daily life. The study findings are more pertinent for consumers and businesses. Consumers are more likely to embrace FinTech when they perceive it as easy to use, beneficial to their performance and supported by adequate resources. Conversely, companies may utilise the study's results and implications to create FinTech solutions that are user-friendly, supported by robust support systems and in line with the requirements and expectations of their target market. Companies may increase adoption rates and interaction with their FinTech products by concentrating on improving user experience and promoting a good social impact, hence guaranteeing more success in the market.

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