

Original Article

Key Drivers of Fintech Adoption Among Pakistani MSMEs

Erum Fatima (Corresponding Author)

Department of Management Sciences
DHA Suffa University, Karachi, Pakistan

<https://orcid.org/0009-0000-2213-8949>

erumfatimaaliraza@gmail.com

Kamran Khan (Ph.D)

Department of Management Sciences
DHA Suffa University, Karachi, Pakistan

<https://orcid.org/0000-0001-9963-0616>

kamranabbaskhan@gmail.com

Raazia Gul (Ph.D)

Faculty of Management Sciences
SZABIST University, Islamabad, Pakistan

<https://orcid.org/0000-0002-4909-7902>

raazigul@gmail.com

Article history:

Received: March 26, 2025

Revised: June 08, 2025

Accepted: June 11, 2025

Published: July 01, 2025

Authors' Biography

Erum Fatima is a Ph.D Scholar at the Department of Management Sciences, DHA Suffa University in Karachi, Pakistan. She completed her Masters in Business Administration from Hamdard University in Karachi, Pakistan.

Kamran Khan (Ph.D) is an Associate Professor at the Department of Management Sciences, DHA Suffa University in Karachi, Pakistan. He obtained his Doctorate in Business Administration from Iqra University in Karachi, Pakistan.

Raazia Gul (Ph.D) is an Assistant Professor at the Faculty of Management Sciences, SZABIST University in Islamabad, Pakistan. She obtained her Doctorate in Business Administration from Foundation University in Islamabad, Pakistan.

JEL Classification: **G21, O33, L26, M15**

How to Cite:

Fatima, E., Khan, K., & Gul, R. (2025). Key Drivers of Fintech Adoption Among Pakistani MSMEs. *Bulletin of Multidisciplinary Studies*, 2(2), 146–158. <https://doi.org/10.5281/zenodo.15898139>

Publisher's Note:

International Research and Publishing Academy (iRAPA) stands neutral with regard to jurisdictional claims in the published maps and institutional affiliations.

Copyright:

© 2025 Bulletin of Multidisciplinary Studies published by International Research and Publishing Academy (iRAPA)



This is an Open Access article published under the Creative Commons Attribution 4.0 International (CC BY 4.0) (<https://creativecommons.org/licenses/by/4.0>)

Creative Commons Attribution (CCBY): lets others distribute and copy the article, to create extracts, abstracts, and other revised versions, adaptations or derivative works of or from an article (such as a translation), to include in a collective work (such as an anthology), to text or data mine the article, even for commercial purposes, as long as they credit the author(s), do not represent the author as endorsing their adaptation of the article, and do not modify the article in such a way as to damage the author's honour or reputation.

ABSTRACT

The adoption of financial technology by micro, small, and medium enterprises enhances their operational efficiency, improves financial accessibility, and financial inclusion in developing economies. The factors scrutinized for fintech adoption in this research are categorized into technology, organization, and environment context, including relative advantage, complexity, compatibility, top management support, organization readiness, readiness of trading partners, competitive pressure, and standard uncertainty. Primary data was gathered by disseminating a self-administered structured survey, and the responses were analyzed. The findings of the study reveal that all three elements of the TOE model positively influence fintech adoption, with the organization component being the highest predictor among the three. The research findings validate that TOE factors contribute significantly towards fintech adoption among Pakistani MSMEs. This research intends to enrich the literature on firm-level adoption, an underexplored area, especially in the context of developing and underdeveloped countries. The conclusions drawn from this study provide imperative insights for the government, policymakers, and fintech firms.

Keywords: Access to credit, Digital payments, Financial technology adoption, MSMEs, Technological change

INTRODUCTION

During the past decade, the operations of Small and Medium Enterprises (SMEs) have been greatly impacted by technological advancements (Shahadat et al., 2023). This digital transformation of businesses plays an imperative role in initiating competitiveness. Information and communication technology adoption (ICT) increases SME's capability to improve quality, reduce production costs, and quick and easy flow of information to gain a competitive advantage (Zide & Jokonya, 2022). One of the recent technological innovations that has impacted businesses is the adoption of financial technology, abbreviated as "Fintech". It is an amalgamation of the two terms "financial services" and "digital technology". Fintech has transmuted the global financial setting by providing efficient and accessible financial services using digital technologies. This technological advancement has impacted every facet of life and has changed the way individuals and businesses plan and manage their finances. Fintech comprises a variety of innovations, including digital payments, crowdfunding, mobile banking, peer-to-peer lending, insurance, agritech, and blockchain, to name a few. These revolutions in the financial sector are challenging traditional financial services and access to financial tools, particularly for the unbanked and underserved segments, including women entrepreneurs and micro, small, and medium enterprises (MSMEs). (Yáñez-Valdés & Guerrero, 2023; Firmansyah et al., 2023).

MSMEs involve almost all corporations universally, playing a vital role in developing markets and nurturing inventions. The sorting of MSMEs into categories differs among countries and institutions. The different criteria based on which the distinction is made include capital investment, annual revenue, and number of

employees, or a combination of these factors is also used. The European Commission defines SMEs based on employees, annual revenue, or balance sheet total. Companies with a workforce of less than 250 individuals are considered SMEs by the International Finance Corporation (IFC) (Kumar et al., 2023). Small and Medium Enterprise Development Authority (SMEDA) describes micro enterprises are those with fewer than 10 employees and total assets under 2 million rupees, small enterprises are categorized as having 10 - 35 employees and total assets between 2 and 20 million rupees, and medium enterprises are defined as those having employees between 36 and 99 and total assets between 20 and 40 million rupees. As per a United Nations (UN) article, the labor force worldwide will entail six hundred million new openings by 2030, emphasizing the imperative significance of stressing the expansion of SMEs for regimes globally (Kumar et al., 2023; Kumar et al., 2024).

MSMEs are vital to Pakistan's economic growth, accounting for approximately 40% of the GDP of country and 26% of the exports in the manufacturing sector. Despite their substantial role, MSMEs face numerous challenges, including inadequate resources, lack of technical skills and support, outdated manufacturing facilities, and lack of financial literacy, but among these, access to finance is a significant obstacle (Khaliq et al., 2022). Despite all the potential benefits that financial technology offers, the adoption of fintech is relatively low among MSMEs in Pakistan, and by the end of 2022, approximately 72% of the businesses were unaware of fintech and hence a low rate of adoption. Moreover, the literature that exists on fintech adoption in Pakistan mostly relates to consumer adoption and secondary data (Ashraf et al., 2022; Qaiser & Fahad, 2024). Very limited research is done on the adoption of fintech by banks and other financial institutions

(Ahmed et al., 2024). Based on this disparity, the study aspires to fill this vacuum by probing the factors that impact the financial technology adoption at the firm level, employing the TOE model. Aligned with the purpose of the study, the following research questions are proposed.

- To what extent does the technological element of the TOE model impact the adoption of fintech by MSMEs?
- How does the organizational element of the TOE model contribute to fintech adoption by MSMEs?
- How does the TOE model's environmental element affect fintech adoption by MSMEs?

The fundamental goal of this research is to scrutinize the liaison between technological, organizational, and environmental elements of the TOE model on the financial technology adoption of MSMEs in Pakistan. The research scope is restricted to the MSMEs operating in Pakistan, and the research unit of analysis is the owners/decision makers of these MSMEs. The outcomes and results of this research will help policymakers, financial institutions, researchers, and regulators like the State Bank of Pakistan, SMEDA, Chamber of Commerce, and SECP to better formulate policies that enhance fintech adoption among MSMEs in Pakistan, resulting in achieving digitalization of the economy and improved financial inclusion. The study complements the academic literature on fintech adoption.

The subsequent sections of the paper are systematized as follows: Literature review built on the TOE model and hypothesis formulation. The next section presents the research methodology, including sampling technique and instrument formulation. The succeeding section discusses the data evaluation and results of PLS-SEM. The last segment deliberates on the study's findings, discusses limitations, offers practical propositions, and recommends forthcoming research directions.

LITERATURE REVIEW

Businesses' adoption of financial technology has surfaced as a significant enabler for growth and sustainability. According to Venkatesh et al. (2003) UTAUT and other conventional models like Davis (1989) TAM, explain how individuals adopt and use novel technology. The Technology-Organization-Environment (TOE) Model (Tornatzky & Klein, 1982) explains the adoption of technology from the enterprise perspective meticulously, as it divides the factors into three substantial elements. Several studies

on firms' technology adoption have utilized this model to explain the adoption of novel technologies in recent times. Chittipaka et al. (2023) adopted the TOE model to analyze the blockchain adoption by India's supply chains, confirming that the adoption of blockchain improves organizational performance and trust. Grounded on the TOE framework, the adoption of social robots by SMEs was studied, and their subsequent impact on SMEs' performance was analyzed (Islam et al., 2025). The Tanzanian bank's adoption of big data analytics was also studied using the TOE framework (Mwemezi & Mandari, 2024). The underpinning theory adopted for this study is the TOE framework recommended by (Tornatzky & Klein, 1982). This model is adopted as it is best suited to study the technology adoption in an enterprise context (Abed, 2020).

Financial Technology Adoption

Financial Technology is termed as digital innovations in the financial sector (Philippon, 2019). It is often misunderstood as an app, but in reality, fintech encompasses a variety of novel innovations, including digital wallets, mobile banking, p2p lending, crowdfunding, blockchain, mobile payment systems, cloud computing, and robo-advisors. The application of fintech has impacted almost every industry. Fintech adoption is portrayed as a process through which businesses and end users adopt and amalgamate digital financial tools and services into their business operations. By leveraging digital platforms, microfinance institutions can shorten loan application procedures and can serve small businesses in unbanked and remote areas that are often ignored by traditional lenders because of a lack of guarantees or credit history requirements (Omowole et al., 2024).

Technological Elements and Fintech Adoption

The adoption of any novel technology is driven by the potential benefits it offers to an organization. The chances of adoption increase when organizations perceive the novel technology to be better than the existing ones, how well the new technology can integrate into the existing systems, and how easy the technology is to understand and use. The choice to adopt a mobile payment platform will be grounded on how easy it is to use by all stakeholders, including customers. Ojo et al. (2023) reported that the ease of use of mobile payment systems positively influences their adoption among Malaysian merchants. Bag et al., (2022) also reported that relative advantage and compatibility have a considerable impact on the adoption of blockchain technology. Khan et al., (2021) indicated

that compatibility and relative advantage play a major and positive role in SME mobile payment adoption. Ekasari et al. (2021) verified that the technological component of the TOE model has a strong influence on Indonesian SMEs to adopt a cashless payment system. Building on the exceeding conversation, the research inquiry proposes the subsequent hypothesis.

H₁: Technology significantly influences MSMEs' financial technology adoption

Organizational Elements and Fintech Adoption

This research study considers the two factors to investigate the impact of organizational elements on fintech adoption. The two factors are top management support and organizational preparedness. Review of previous literature confirms that the assistance of top management is imperative for embracing technology since it deals with the scope of managers' comprehension and competence in adopting new technology (Maroufkhani et al., 2022; Mukherjee & Chittipaka, 2022). Numerous studies on technology adoption prove a positive and substantial relationship between top management support and intention to adopt technology, including studies on blockchain technology (Bag et al., 2022), cloud computing adoption and big data analytics adoption (Maroufkhani et al.,

2022). Grounded on the discussion above, the current study articulates the following hypothesis:

H₂: Organization significantly influences MSMEs' financial technology adoption

Environmental Elements and Fintech Adoption

The environment element consists of the factors that impact organizations from the external environment. It includes pressure from competitors, the willingness of trading partners in the supply chain, and standard uncertainty about the new technology adoption. The competitive pressure is a significant predictor of technology adoption. (Bag et al., 2022; Shahadat et al., 2023) indicated that competitor pressure plays a crucial part in predicting organizational intention to adopt technology. Salimon et al., (2021) found in their study that pressure from competitors and trading readiness are vital predictors in m-commerce adoption. Malik et al. (2021) recommends competitor pressure, the readiness of an organization's trading partners, and clarity on standard uncertainty are important for a business's fintech adoption. Established on the above discussion, the research postulates that:

H₃: Environment significantly influences MSMEs' financial technology adoption

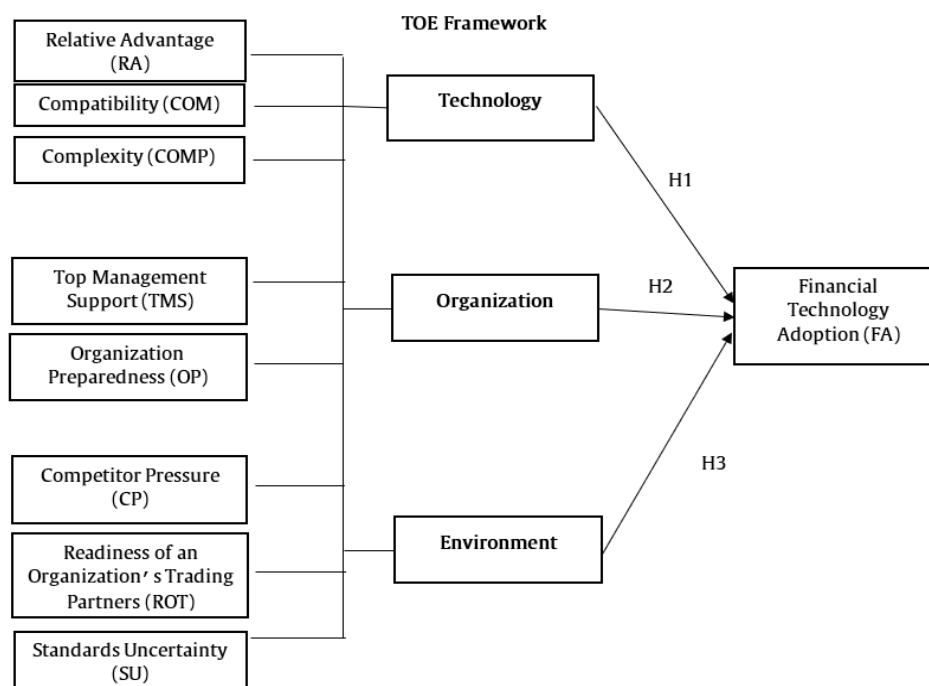


Fig. 1. Conceptual Model

METHODOLOGY

The TOE model comprises three components: technology, organization, and environment. The technology component includes the different types of

tools and technologies that are already in use by the enterprise or are not used by the enterprise but are available in the market to be adopted by the enterprise. The technological component is measured through

three factors: relative advantage, compatibility, and complexity, to study its impact on Pakistani MSMEs' adoption of financial technology. The second factor Compatibility is described as "the degree to which a new system is consistent with the current system within the company" (Maroufkhani et al., 2022, p. 03).

The organizational component is measured by taking organizational readiness (OR) and top management support (TMS). TMS is defined as the assistance offered by the top hierarchy to embrace technology by providing necessary resources and training. Ramdani et al., (2013) explain OR as the existence of indispensable skills, information technology (IT) resources, and systems crucial for technology adoption. The environmental factor is measured by taking competitor pressure, the readiness of an organization's trading partners, and the standards uncertainty. The pressure expressed by the competitors from the industry is called competitive pressure (Picoto et al., 2014). Readiness of an organization's trading partners is stated as the preparedness of the organization's partners to adopt novel technology, and the Standards uncertainty is described as the unavailability of formal regulations commonly imposed by the government for novel technology adoption (Malik et al., 2021).

This research embraces positivist philosophy and utilizes a quantitative research design to scrutinize the causes that impact fintech adoption by MSMEs in Pakistan. The 5.2 million SMEs operating in Pakistan constitute the population for this study. The purposive sampling technique has been utilized to accumulate data by administering the survey form online and offline. The online form was created on Google Docs and distributed through emails to individual businesses and various chambers of commerce in the country, social media platforms, including Facebook business pages, WhatsApp groups, LinkedIn, and Instagram accounts.

The survey form used is separated into three modules. The initial module asked for demographic profile of the study's participants, including education, gender, age, type of industry, and number of employees working in the organization. The following section has questions related to the usage of fintech services over the years. The last module contains questions for the endogenous and exogenous variables measured using a 5-point Likert scale, varying from 1 being "strongly

disagree" to 5 being "strongly agree". The adapted scale is used from the literature. The technology component consists of three factors, and the organizational factors consist of two elements. The items for all these factors are adapted from the research of Badi et al. (2021) and Gangwar et al. (2015).

The third component of the TOE model is Environment, which is measured by three variables, and the items for these variables are adapted from Badi et al., (2021), Gangwar et al., (2015), and Malik et al., (2021). The variable fintech adoption is measured through six items adapted from Salimon et al., (2021). The 525 valid responses are considered a sample of this study, which surpasses the minimum sample requirement based on the 10 times rule. A response rate of 26% was achieved, and the incomplete and invalid responses were identified and deleted using Excel and SPSS software. SmartPLS version 4.0 software was used for advanced data analysis. This study utilizes the PLS-SEM technique to distinguish important constructs that significantly predict fintech adoption. Furthermore, this explanatory research extends a previously established theoretical model, making PLS-SEM an appropriate analytical approach. The analysis is conducted using SmartPLS 4.0.

RESULTS & FINDINGS

The final sample of 525 was utilized for data analysis after removing invalid and incomplete responses. The data was evaluated utilizing IBM SPSS version 27 and SmartPLS version 4.0. The demographic details were examined using SPSS, whereas SmartPLS was used to examine the goodness of data and hypothesis testing.

Demographics

The table below specifies the summary of the demographic statistics of the samples. The demographics analysis disclosed that most of the individuals who took part in the survey are males (71.4%), whereas female respondents are 28.6 %. The majority of the respondents are young and fall into two age groups defined between 26-31 and 32-38 years of age, and the majority of them are graduates or have earned their master's degree. It can be concluded that bulk responses were received from young and educated males.

Table 1
Demographic Analysis of Participants

	Particulars	Frequency	Percentage
Gender	Male	375	71.4
	Female	150	28.6
Age	18-25	111	21.2
	26-31	133	25.3
	32-38	133	25.3
	39-45	90	17.2
	45 and above	58	11.0
Education	SSC/ O LEVEL or equivalent	21	4.0
	HSC/A LEVEL or equivalent	53	10.1
	GRADUATE	168	32.0
	Masters	220	41.9
	POSTGRADUATE	63	12.0
Number of Employees	less than 10 employees	214	40.8
	between 10-35 employees	86	16.4
	between 36-99 employees	225	42.8
Frequency of using FinTech applications	Daily	221	42.1
	From 2 to 3 times a week	106	20.2
	From 4 to 6 times a week	33	6.3
	Once a week	66	12.6
	Once a month	37	7.0
	A few times a year	62	11.8
Number of years using FinTech applications	Less than 2 years	197	37.5
	From 3 to 4 years	164	31.2
	From 5 to 7 years	86	16.4
	More than 7 years	78	14.9
Type of Industry	Restaurants	8	1.5
	Manufacturing	55	10.5
	Pharmaceutical	3	0.6
	Retail	108	20.6
	Supply chain	20	3.8
	Telecommunication	19	3.6
	Transport	10	1.9
	Financial Institutions	70	13.3
	Textile	38	7.2
	Education	55	10.5
	Food & Beverage	32	6.1
	Construction	8	1.5
	Services	50	9.5
	Health Care	8	1.5
	Information & Communication Technologies	25	4.8
	Real Estate	4	0.8
Digital Marketing	10	1.9	
Oil & Gas Marketing	2	0.4	

Most of the respondents belong to either micro-firms or medium firms having 36-99 employees in their company. Almost 60% of the respondents have

been using fintech services for the last 4 years. Out of 525 respondents, 221 (42.1%) are using these services daily and almost 21% of respondents are using fintech

services 2 to 3 times a week. The respondents are almost from all types of industry with the highest from the retail sector as digital payments are gaining more acceptance than other fintech services. The next sector is financial institutions followed by education and manufacturing companies. Many educational institutes are using mobile apps, and digital banking to gather fees from students. The least representation is from oil and gas marketing sector (0.4%) and pharmaceutical companies (0.6%).

Measurement Model

The first step in SmartPLS is to evaluate the measurement model. The outer loadings for all the items should be greater than 0.708 (Legate et al., 2023), which is displayed in Table 2. The scrutiny shows that all the values surpass the threshold of 0.708 except for CP1 (0.674), ROT3 (0.672), and TMS1 (0.636), but these items are not deleted as proposed by Hair Jr et al., (2021), the loadings that fall between 0.4-0.7 are only deleted if they improve the reliability measures.

Table 2
Measurement Indicators

Constructs	Items	Factor Loadings	VIF	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)	R Square
COM	COM1	0.768	1.748	0.892	0.895	0.700	
	COM2	0.829	2.287				
	COM3	0.880	2.863				
	COM4	0.837	2.913				
	COM5	0.865	3.278				
COMP	COMP2	0.889	2.113	0.882	0.889	0.808	
	COMP3	0.918	3.031				
	COMP4	0.889	2.692				
CP	CP1	0.674	1.365	0.850	0.860	0.698	
	CP2	0.917	3.373				
	CP3	0.854	2.523				
	CP4	0.877	2.654				
FA	FA1	0.852	2.677	0.948	0.949	0.793	0.297
	FA2	0.894	3.757				
	FA3	0.916	4.701				
	FA4	0.922	4.656				
	FA5	0.871	3.397				
	FA6	0.887	3.687				
OP	OP1	0.876	2.877	0.899	0.900	0.768	
	OP2	0.882	3.040				
	OP3	0.893	3.204				
	OP4	0.855	2.687				
RA	RA1	0.810	1.994	0.873	0.877	0.725	
	RA2	0.894	2.699				
	RA3	0.897	2.802				
	RA4	0.800	1.878				
ROT	ROT	0.896	2.782	0.765	0.787	0.690	
	ROT2	0.903	2.857				
	ROT3	0.672	1.197				
SU	SU1	0.855	1.886	0.711	0.712	0.636	
	SU2	0.718	1.168				
	SU3	0.814	1.821				
TMS	TMS1	0.636	1.377	0.835	0.855	0.678	
	TMS2	0.892	3.043				
	TMS3	0.878	3.226				
	TMS4	0.860	2.208				

The results in Table 2 present that all AVE values are more than 0.5, the least AVE value of 0.636 is reported for SU, and the maximum AVE value of 0.874 is reported

Next Variance inflation factor (VIF) is reported to check the multicollinearity issues. Multicollinearity does not exist if VIF values are below 5 (Hair Jr et al., 2021). The findings reveal that VIF values for all the items are less than the threshold of 5, hence, no multicollinearity issue exists in the data. Cronbach's Alpha and Composite reliability values are used to inspect the reliability of the data. The reliability of the data is established if the Cronbach's alpha value and CR are above 0.7, whereas values exceeding 0.9 are suggestive of high-quality data. Table 2 displays that the Cronbach Alpha values exceed the base of 0.7 for all the constructs, the least being 0.711 for SU to 0.948 for the construct FA. Similarly, the CR values for all the constructs meet the criteria of 0.7, the least being 0.712 for the construct SU, and the highest CR value is 0.953 for the construct BS. Convergent validity is gauged by computing the average variance extracted (AVE), and the AVE values should be equal to or larger than 0.5 to establish convergent validity (Cheung et al., 2024).

for BS Construct, establishing convergent reliability for the data.

Table 3
Discriminant Validity through Fornell-Larcker Criterion

	COM	COMP	CP	FA	OP	RA	ROT	SU	TMS
COM	0.837								
COMP	0.450	0.899							
CP	0.317	0.087	0.836						
FA	0.298	0.105	0.398	0.891					
OP	0.227	-0.010	0.456	0.435	0.877				
RA	0.697	0.484	0.321	0.227	0.144	0.852			
ROT	0.310	0.168	0.670	0.404	0.365	0.259	0.831		
SU	0.173	0.175	0.381	0.225	0.114	0.192	0.465	0.798	
TMS	0.198	-0.060	0.405	0.434	0.774	0.110	0.316	0.117	0.823

The Fornell-Larcker criterion is examined to check the discriminant validity of all the constructs. In this research, it is ensured that all the constructs are measuring unique concepts and there are no correlation issues (Hair, Jr et al., 2021; Fornell & Larcker, 1981). Table 3 displays values obtained by SmartPLS

for discriminant validity in the diagonal through Fornell-Larcker criteria. The diagonal values for all the constructs are larger than the values to the left of it or below it, hence fulfilling the standards (Hamid et al., 2017).

Table 4
Discriminant Validity through HTMT Correlations

	COM	COMP	CP	FA	OP	RA	ROT	SU	TMS
COM									
COMP	0.497								
CP	0.367	0.114							
FA	0.323	0.113	0.443						
OP	0.254	0.029	0.522	0.470					
RA	0.788	0.546	0.371	0.249	0.164				
ROT	0.379	0.199	0.829	0.473	0.432	0.314			
SU	0.215	0.215	0.495	0.274	0.197	0.237	0.646		
TMS	0.231	0.089	0.480	0.488	0.893	0.131	0.402	0.281	

The study also uses hetero- and mono-trait (HTMT) correlations, which should be less than 0.90 (Henseler et al., 2015). Table 4 confirms that all HTMT values are less than 0.9, hence, discriminant validity is established for the data. As all the thresholds for reliability and validity are met, it can be concluded that the goodness of the data is established. Table 2 presents the R-squared

values. R-squared is a measure of the fitness of the model and explains the variance of the endogenous variables. The analysis of the R-squared measure reveals that the exogenous variables, including technology, organization, and environment, explain 29.7% of the variation in fintech adoption.

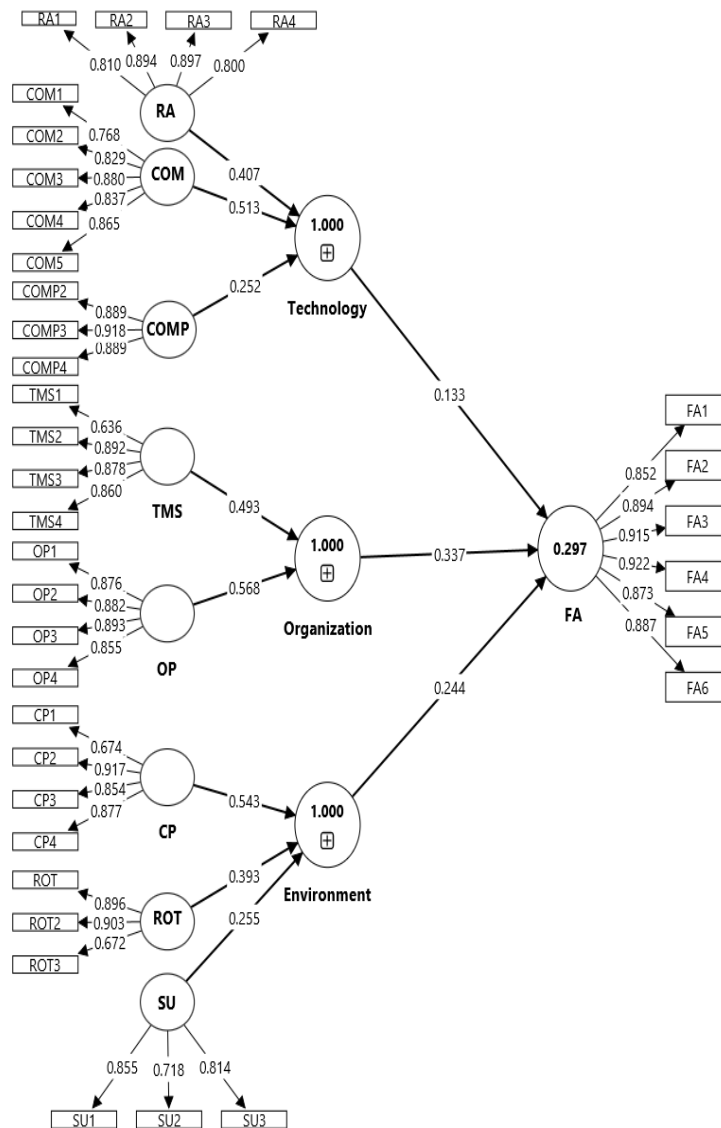


Fig. 2. Factor Loadings

Structural Model

For evaluating the hypothesis, the standard bootstrapping was applied using 5000 subsamples.

Table 5
Hypothesis Results

Hypothesis	Original sample (O)	Sample mean (M)	T statistics	P values	Decision
H ₁ : Technology -> FA	0.133	0.134	2.838	0.005	Accepted
H ₂ : Organization -> FA	0.337	0.334	5.885	0.000	Accepted
H ₃ : Environment -> FA	0.244	0.245	3.805	0.000	Accepted

Table 5 displays the path coefficient results, including beta values, T statistics, and P values for all the hypotheses established.

Discussion

The study tested three proposed hypotheses. The first hypothesis tested the relationship between technology components and fintech adoption. The p-value is 0.005, which is less than 0.05, and the t-statistic is also above 2, hence, it is statistically significant. The first hypothesis for this study is accepted, and it can be concluded that technology positively and significantly influences

MSMEs' decision to adopt fintech. The beta value of 0.133 indicates that the technology impacts fintech adoption by 13.3% positively. The findings support the previous literature, which emphasizes the critical role of technological factors in driving fintech adoption among businesses (Bag et al., 2022; Kumar et al., 2022; Ekasari et al., 2021). Economically, the positive and significant relationship between technology and

fintech adoption among Pakistani MSMEs suggests that businesses with greater technological preparedness are more likely to embrace fintech solutions. The second hypothesis states the relationship between the organizational element of the TOE model and fintech adoption. The p-value is 0.000 and the t-statistic is 5.885, surpassing the established thresholds, hence H2 is also accepted. The organizational factor impacts fintech adoption positively by 33.7%. This finding supports earlier research (Shahadat et al., 2023; Kumar et al., 2022; Ekasari et al., 2021). From an economic perspective, better-prepared business organizations are more likely to embrace fintech, leading to greater efficiency and smarter financial decisions. This highlights the significance of capacity-building efforts and leadership training to help MSMEs make the most of fintech solutions.

The role of TMS in adoption has been validated by many studies on the adoption of technology (Nguyen et al., 2022; Maroufkhani et al., 2023). The third hypothesis is also accepted as the p-value < 0.05 and the t-statistic > 2.0, as exhibited in Table 5. The analysis specifies that the environmental factor of the TOE model impacts the MSME's decision to adopt fintech by 24.4%. The hypothesis is established, and the results are consistent with numerous studies on technology adoption (Ekasari et al., 2021; Kumar et al., 2022; Mujahed et al., 2021). The pressure from customers and trading partners both are considered a vital predictor of technology adoption (Bag et al., 2022; Salimon et al., 2021).

CONCLUSION

The research investigated the crucial factors influencing financial technology (fintech) adoption among MSMEs in Pakistan using the Technology-Organization-Environment framework. The findings verify that all the hypothesized relationships are supported, indicating that compatibility, relative advantage, Organizational readiness, top management support, competitor pressure, and readiness of trading partners substantially influence fintech adoption among MSMEs. The results indicate the importance of both internal and external factors in enhancing fintech adoption and augmenting the vital role of digital adoption in MSME progression and viability. The findings corroborate the previously published literature. Adoption is faster when businesses perceive that adoption will reap more rewards in the form of improving operational efficiency, reducing cost, and enhancing customer service. Relative advantage and compatibility play a crucial role in adoption decisions and are considered vital predictors of technology

adoption.

The organizational elements, such as top management support and organizational readiness to adopt technology, play an impact role in adoption. The study highlights the importance of the acceptance of technology by the leadership of the organization, as when the leader is ready to embrace the novel technology, it will motivate and provide resources for all to prepare for the adoption of technology. The organizational element has the highest impact on fintech Adoption. Moreover, the readiness of the partners in the supply chain and competitors' adoption also play a crucial role in preparing organizations to adopt technology to remain in the competition. This strengthens the robustness of our findings and endorses the relevance of the TOE framework in understanding fintech adoption among MSMEs in Pakistan.

It is worth noting that several respondents are from the retail sector, where digital payments are the main fintech services being used. It suggests that future research should be conducted specifically on individual fintech services to better understand the fintech adoption dynamics in Pakistan. Theoretically, the study adds to the literature by validating the impact of all TOE factors on fintech adoption in MSMEs in Pakistan and provides practical insights into going digital for MSME operations. Like other published studies, this study is also not free from limitations. First, the cross-sectional data were collected for examining adoption due to time and budget constraints through a self-reported survey, which may have introduced response bias. Second, the research is limited to the geographical boundaries of Pakistan, which may influence the generalizability of results with advanced and more technologically savvy economies. Lastly, the TOE framework provides a broad model for studying technology adoption; additional variables like trust, regulatory assistance, and financial literacy could be investigated to improve its predictive power and provide further insights into the fintech adoption behavior of MSMEs. The applicability of the findings can be validated by investigating the fintech adoption factors in other economies by future researchers.

This study provides rational evidence on the dynamics of fintech adoption among MSMEs in Pakistan. The research adds to both industry and academia by corroborating with earlier research and presenting practical suggestions. The research has both managerial and government-level implications, where there is a need to further improve the financial technology knowledge and the benefits it offers to boost its adoption. Financial institutions and fintech

service providers should arrange workshops and training for MSME owners to motivate them to adopt these technologies and establish resilient businesses that can survive in turbulent times such as the COVID-19 pandemic. Policymakers should work on reducing regulatory ambiguities and improving digital infrastructure throughout the country. Moreover, MSMEs should also come forward and prepare their organizations to embrace digital technologies. While fintech adoption persists in enhancing the MSME setting, financial institutions, businesses, policymakers, and regulators must foster an ecosystem that encourages digital adoption and fosters MSMEs' sustainability.

Competing Interest

The authors had no competing interests.

References

- Abed, S. S. (2020). Social commerce adoption using TOE framework: An empirical investigation of Saudi Arabian SMEs. *International Journal of Information Management*, 53, 102118.
<https://doi.org/10.1016/j.ijinfomgt.2020.102118>
- Ahmed, M., Kumar, A., Talha, M., Akram, Z., & Arif, K. (2024). Impact of fintech on the Pakistani banking sector. *Journal of Economic Info*, 11(1), 1-14.
<https://doi.org/10.31580/ek5dnd23>
- Ashraf, M., Hafeez, R., & Sajid, A. N. (2022). *Factors affecting the adoption of Fintech in Pakistan based on the Unified Theory of Acceptance and Use of Technology Model: An empirical study on financial inclusion in Pakistan*. 1, 9-26.
<https://doi.org/10.52461/jftis.v1i1.1793>
- Badi, S., Ochieng, E., Nasaj, M., & Papadaki, M. (2021). Technological, organisational and environmental determinants of smart contracts adoption: UK construction sector viewpoint. *Construction Management and Economics*, 39(1), 36-54.
<https://doi.org/10.1080/01446193.2020.1819549>
- Bag, S., Rahman, M. S., Gupta, S., & Wood, L. C. (2022). Understanding and predicting the determinants of blockchain technology adoption and SMEs' performance. *The International Journal of Logistics Management*, 34(6), 1781-1807.
<https://doi.org/10.1108/IJLM-01-2022-0017>
- Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41(2), 745-783.
<https://doi.org/10.1007/s10490-023-09871-y>
- Chittipaka, V., Kumar, S., Sivarajah, U., Bowden, J. L. H., & Baral, M. M. (2023). Blockchain Technology for Supply Chains operating in emerging markets: an empirical examination of technology-organization-environment (TOE) framework. *Annals of Operations Research*, 327(1), 465-492.
<https://doi.org/10.1007/s10479-022-04801-5>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, 13(3), 319-339.
<https://doi.org/10.2307/249008>
- Ekasari, N., Rosmeli, R., & Syafri, R. A. (2021, August). Digital Cashless Payment Readiness Model on MSMEs Using Technological-Organization-Environment (TOE) Framework: Study on MSME Users Gopay and Ovocash. In *The 3rd Green Development International Conference (GDIC 2020)* (pp. 238-244). Atlantis Press.
<https://doi.org/10.2991/aer.k.210825.043>
- Firmansyah, E. A., Masri, M., Anshari, M., & Besar, M. H. A. (2023). Factors Affecting Fintech Adoption: A Systematic Literature Review. *FinTech*, 2(1), Article 1.
<https://doi.org/10.3390/fintech2010002>
- Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research*, 18(3).
<https://doi.org/10.1177/002224378101800313>
- Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, 28(1), 107-130.
<https://doi.org/10.1108/JEIM-08-2013-0065>
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (p. 197). Springer Nature.
- Hamid, M. R. A., Sami, W., & Sidek, M. H. M. (2017). Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. *Journal of*

- Physics: Conference Series*, 890(1), 012163.
<https://doi.org/10.1088/1742-6596/890/1/012163>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
<https://doi.org/10.1007/s11747-014-0403-8>
- Islam, N., Rakshit, S., & Paul, T. (2025). Antecedents and consequences of social robots adoption for SMEs—Reimagining emerging technologies in the context of the new normal. *Technological Forecasting and Social Change*, 210, 123887.
<https://doi.org/10.1016/j.techfore.2024.123887>
- Khaliq, A., Islam, M. S. U., Akram, M., Hussain, A., & Usman, M. (2022). Factors Affecting Small and Medium-Sized Enterprises' Accessibility to Institutional Finance in Pakistan: Moderating Role of Government Support. *South Asian Journal of Management Sciences*, 16(1).
<https://doi.org/10.21621/sajms.2022161.06>
- Khan, N. A., Khan, A. N., Bahadur, W., & Ali, M. (2021). Mobile payment adoption: A multi-theory model, multi-method approach and multi-country study. *International Journal of Mobile Communications*, 19(4), 467.
<https://doi.org/10.1504/ijmc.2021.116119>
- Kumar, A., Singh, R. K., & Swain, S. (2022). Adoption of Technology Applications in Organized Retail Outlets in India: A TOE Model. *Global Business Review*, 09721509211072382.
<https://doi.org/10.1177/09721509211072382>
- Kumar, D., Phani, B. V., Chilamkurti, N., Saurabh, S., & Ratten, V. (2023). Filling the SME credit gap: A systematic review of blockchain-based SME finance literature. *Journal of Trade Science*, 11(2/3), 45–72.
<https://doi.org/10.1108/JTS-06-2023-0003>
- Kumar, J., Rani, G., Rani, M., & Rani, V. (2024). Blockchain technology adoption and its impact on SME performance: Insights for entrepreneurs and policymakers. *Journal of Enterprising Communities: People and Places in the Global Economy*, 18(5), 1147–1169.
<https://doi.org/10.1108/JEC-02-2024-0034>
- Legate, A. E., Hair Jr, J. F., Chretien, J. L., & Risher, J. J. (2023). PLS-SEM: Prediction-oriented solutions for HRD researchers. *Human Resource Development Quarterly*, 34(1), 91–109.
<https://doi.org/10.1002/hrdq.21466>
- Malik, S., Chadhar, M., Vatanasakdakul, S., & Chetty, M. (2021). Factors affecting the organizational adoption of blockchain technology: Extending the technology–organization–environment (TOE) framework in the Australian context. *Sustainability*, 13(16), 9404.
<https://doi.org/10.3390/su13169404>
- Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2022). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*, 123(1), 278–301.
<https://doi.org/10.1108/IMDS-11-2021-0695>
- Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*, 123(1), 278–301.
<https://doi.org/10.1108/IMDS-11-2021-0695>
- Mujahed, H. M. H., Musa Ahmed, E., & Samikon, S. A. (2022). Factors influencing Palestinian small and medium enterprises intention to adopt mobile banking. *Journal of Science and Technology Policy Management*, 13(3), 561–584.
<https://doi.org/10.1108/JSTPM-05-2020-0090>
- Mukherjee, S., & Chittipaka, V. (2022). Analysing the adoption of intelligent agent technology in food supply chain management: an empirical evidence. *FIIB Business Review*, 11(4), 438–454.
<https://doi.org/10.1177/23197145211059243>
- Mwemezi, J., & Mandari, H. (2024). Big data analytics usage in the banking industry in Tanzania: Does perceived risk play a moderating role on the technological factors. *Journal of Electronic Business & Digital Economics*, 3(3), 318–340.
<https://doi.org/10.1108/JEBDE-01-2024-0001>
- Nguyen, T. H., Le, X. C., & Vu, T. H. L. (2022). An extended technology–organization–environment (TOE) framework for online retailing utilization in digital transformation: Empirical evidence from Vietnam. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(4), 200.
<https://doi.org/10.3390/joitmc8040200>
- Ojo, A. O., Fawehinmi, O., Tan, C. N.-L., & Ojo, O. T. (2023). Merchant adoption intention of mobile

- payment platforms in Malaysia. *Journal of Systems and Information Technology*, 26(1), 31–50.
<https://doi.org/10.1108/JSIT-08-2022-0200>
- Omowole, B., Urefe, O., Mokogwu, C., & Ewim, S. (2024). Integrating fintech and innovation in microfinance: Transforming credit accessibility for small businesses. *International Journal of Frontline Research and Reviews*, 3, 090–100.
<https://doi.org/10.56355/ijfr.2024.3.1.0032>
- Philippon, T. (2019). The FinTech Opportunity. In *The Disruptive Impact of FinTech on Retirement Systems*.
<https://doi.org/10.1093/oso/9780198845553.003.0011>
- Picoto, W., Belanger, F., & Palma-dos-Reis, A. (2014). A technology-organisation-environment TOE-based m-business value instrument. *International Journal of Mobile Communications*, 12(1), 78–101.
<https://doi.org/10.1504/IJMC.2014.059240>
- Kaiser, H., & Fahad, M. (2024). Fintech in Pakistan: Current landscape, challenges, and global insights. *Bulletin of Business and Economics (BBE)*, 13(3), 48–53.
<https://doi.org/10.61506/01.00442>
- Ramdani, B., Chevers, D., & Williams, D. A. (2013). SMEs' adoption of enterprise applications: A technology-organisation-environment model. *Journal of Small Business and Enterprise Development*, 20(4), 735–753.
<https://doi.org/10.1108/JSBED-12-2011-0035>
- Salimon, M. G., Kareem, O., Mokhtar, S. S. M., Aliyu, O. A., Bamgbade, J. A., & Adeleke, A. Q. (2021). Malaysian SMEs m-commerce adoption: TAM 3, UTAUT 2 and TOE approach. *Journal of Science and Technology Policy Management*.
<https://doi.org/10.1108/JSTPM-06-2019-0060>
- Shahadat, M. H., Nekmahmud, M., Ebrahimi, P., & Fekete-Farkas, M. (2023). Digital technology adoption in SMEs: what technological, environmental and organizational factors influence in emerging countries?. *Global Business Review*, 09721509221137199.
<https://doi.org/10.1177/09721509221137199>
- Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on engineering management*, (1), 28–45.
<https://doi.org/10.1109/TEM.1982.6447463>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, 27(3), 425–478.
<https://doi.org/10.2307/30036540>
- Yáñez-Valdés, C., & Guerrero, M. (2023). Assessing the organizational and ecosystem factors driving the impact of transformative FinTech platforms in emerging economies. *International Journal of Information Management*, 73, 102689.
<https://doi.org/10.1016/j.ijinfomgt.2023.102689>
- Zide, O., & Jokonya, O. (2022). Factors affecting the adoption of Data Management as a Service (DMaaS) in Small and Medium Enterprises (SMEs). *Procedia Computer Science*, 196, 340–347.
<https://doi.org/10.1016/j.procs.2021.12.022>