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Fintech Implementation Success: An Integrated DOI–RBV Perspective

Harsha Pungaliya, Dr Akash Sharma, Dr Sumeet Gupta*

Research Scholar, School of Business (SoB), University of Petroleum & Energy Studies, Kandoli Via Premnagar, Dehradun-248007, India

Assistant Professor, Parul Institute of Management and Research (PIMR), Parul University, Waghodia, Vadodara, Gujarat-391760, India

Assistant Professor, School of Business (SoB), University of Petroleum & Energy Studies, Kandoli Via Premnagar, Dehradun-248007, India

Professor, Cluster Head and Associate Dean, School of Business (SoB), University of Petroleum and Energy Studies, Kandoli Via Premnagar, Dehradun-248007, India

Abstract:

Fintech Implementation is crucial for economic growth and performance for any financial institution. Fintech success drivers impacting implementation remain underexplored in India. Prior studies have focused more on consumer adoption, using models- TAM and UTAUT. This study focuses on Fintech success drivers from an industry perspective, examining the influence on earnings and growth as performance indicators through an integrated Diffusion of Innovation Theory and Resource-Based View theory, capturing both external diffusion and internal resources. The research analyses a primary survey of Fintech experts across diverse sectors in India. The DOI–RBV implementation success model provides policymakers, fintech practitioners, and financial institutions with actionable insights for sustainable development.

Keywords: Fintech, Implementation, Fintech success driver, DOI- RBV

JEL Classification Number: G21, G 23, O33, L86

I. Introduction

Fintech innovation is reshaping the entire financial world and has impacted financial services, imposing challenges for traditional financial institutions. In recent years, consumers have eagerly adopted fintech, prompting financial companies and banks to accelerate Fintech innovation and implementation to meet rising expectations [1], [2]. Since 2015, India has witnessed a rapid expansion of Fintech innovation and financial institutions leveraging new technologies to uplift services, transform operations, and address structural challenges. Fintech contributes to improving legacy systems, developing new technological capabilities, and implementing the right technology that transforms Indian financial Institutions (BCG & QED Investors, 2024; Saksonova & Kuzmina- Merlino, 2017; Zafar et al., 2025).

Despite the rapid growth, the effective implementation of fintech has its success drivers and challenges that hinder industry transformation and Indian economic growth. The key Fintech success drivers include underdeveloped IT expertise, cybersecurity risks, lack of awareness, digital illiterate customers, strict licensing regulations, and illegal or unregulated applications of Fintech [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15]. Unless these drivers are addressed, achieving long-term Fintech success in developing economies like India will remain challenging.

Existing literature has predominantly examined Fintech implementation from a consumer perspective (Silva, 2015; Venkatesh et al., 2003), considering driver trust, user-friendliness, and perceived value, but it does not consider the same at the industry level. Nearly 90% of Fintech ventures fail despite growth in implementation [18]. Current research emphasises that collaboration between Fintech and financial institutions is key to the successful implementation of fintech (Ruhland & Wiese, 2023) and that exploring Fintech success drivers is key to overcoming industry challenges [20].

To address the gap, the present research aims to (1) identify and validate the Fintech drivers for success factors essential for effective implementation and (2) examine the impact on performance outcomes in terms of earnings and growth. To achieve the objectives, the study develops the DOI–RBV Implementation Success Model, which integrates the Diffusion of Innovation theory (DOI) and the Resource-Based View theory (RBV). The DOI captures External innovation diffusion, such as policy, regulation, and partnership, while the RBV captures internal capabilities, including infrastructure, risk, talent, and cybersecurity. The data analysis is done using Confirmatory Composite Analysis -CCA and Partial Least Squares Structural Equation Modelling (PLS-SEM).

II. Literature Review

2.1 Fintech Implementation, Performance and Economic Growth

The effective implementation of Fintech is crucial for impacting the performance of banking institutions & economic growth. According to Aloulou et al. (2024), the implementation of fintech in banking provides numerous benefits for financial inclusion and economic growth. Yuspin & Fauzie (2023) argue that digitalisation encourages financial institutions to improve performance and strengthen corporate governance by implementing Fintech in Sharia banking.

Alsmadi et al. (2023) highlight that fintech enables banking opportunities rather than outright disruption, with some key success drivers /challenges. Stewart & Jürjens (2018) developed adoption constructs such as trust, security, value-added, and user design that influence adoption. But it does not emphasise the firm-level challenges that hinder long-term fintech implementation success.

Yu et al. (2025) highlight that fintech facilitates farmer wealth accumulation and reduces inequality through access to credit, information, and asset allocation; however, the drivers related to costs, efficiency, and fund utilisation hinder effective implementation. In small and medium-sized enterprises (SMEs), fintech enhances operational efficiency and facilitates digital transformation. Soni et al. (2022) emphasise that Industry 4.0 technology and fintech significantly enhance SME performance with certain Fintech success drivers. Effective Fintech implementation is impacting liquidity and risk management in the banking sector. Al-Shari and Lokhande (2023) highlight the identification of risks and Fintech success drivers associated with adopting fintech in banking and their impact on performance, influencing decision-making in banks. Wu et al. (2024) caution during financial crises, fintech adoption is impacting the banking liquidity of traditional banking. It also indicates that the adoption of fintech reduces banking liquidity.Bian et al. (2024) highlight that Fintech adoption is positively impacting traditional banking related to banking risk, digital transformation, and market share, which in turn positively impacts bank performance.

2.2 Fintech Succes Drivers

Fintech success drivers for its effective implementation are transforming towards processes through digitalization. Small and medium-sized enterprises are facing challenges when implementing fintech solutions due to resource constraints and digital illiteracy in developing countries. Akpan et al. (2022) highlight that the lack of technological expertise, infrastructure, and funding hinders the fintech implementation in SMEs, limiting their digital transformation potential.

In the non-banking sector, Micu (2016) examined the implementation of fintech and how it has implemented solutions related to the operation and interaction of Romanian financial services providers and the research indicates about impact on consumers and disruption. Financial services providers are slowly implementing fintech innovations as it has certain issues with respect to widespread adoption and high costs faced by financial service providers in the Romanian non-banking sector.

In Latvia, slow progress, weak supervision, and limited tax incentives have hindered the growth of the fintech sector. Saksonova & Kuzmina-Merlino (2017) emphasize that accelerating Fintech implementation requires targeted policies in platform development, supervision, and fiscal incentives, with collaboration between Fintech firms and traditional businesses offering new opportunities.

In Palestine, the implementation of fintech in banking is hindered by infrastructure gaps, digital illiteracy, and inadequate fintech frameworks. Hurani et al. (2024) utilizing the TOE framework that classifies Fintech success drivers into technological (lack of IT talent, infrastructure, digital illiteracy), organizational (resistance to change, limited funding, lack of digital skills), and environmental (small market size, inadequate Fintech frameworks) but it does not cover firm-specific resource capabilities and diffusion innovation dynamics.

2.3 Theoretical Framework: Addressing Gaps through the DOI and RBV Perspectives

Literature highlights both the opportunities and key success drivers of Fintech adoption but it has not covered how effective it is in terms of innovation and resource utilization as indicated by [16], [17], [32]. It explains a partial organizational perspective [33] but it does not include impact on organizational performance covering the role of external diffusion factors and firm-level resource capabilities.

Rogers (1995) explains innovations spread and other attributes such as relative advantage, compatibility, difficulty, trialability, and observability impact the success of Fintech implementation. DOI highlights that larger financial institutions with greater technological readiness are more likely to implement fintech due to the observable benefits. On the other hand smaller firms perceive complexity as a challenge [35] in Fintech Implementation. But it does not cover the internal resources necessary to achieve success in fintech implementation. The Resource-Based View (RBV) Barney (1991) focuses on specific firm resources: technological, infrastructural, and organizational capabilities, thereby enhancing performance and competitive advantage. RBV helps explain why some firms succeed in leveraging fintech; however it does not cover the external diffusion forces that influence implementation.

Stewart & Jürjens (2018) analysed Fintech adoption through the DOI lens, but they have covered the firm-level resources necessary for successful implementation. Bian et al. (2024) applied RBV to analyze banking performance but not covered the external diffusion forces that drive fintech implementation success.

III. Research Methodology

The present research paper adopts an exploratory and quantitative research design to evaluate the relationship between Fintech success drivers, implementation, and the performance of financial institutions. The study aims to analyse how Fintech success drivers influence Fintech implementation, which further impacts institutions' performance outcomes within the Indian Fintech context. Fintech success drivers and implementation of Fintech constitute a DOI perspective, while the performance of financial institutions is taken from RBV. Both taken together constitute an integrated DOI- RBV perspective.

A structured questionnaire was designed for collecting cross-sectional data at a single point in time based on Fintech adoption, technology implementation, success drivers and performance of financial institutions.

3.1 Data Collection For The Study

The primary data were collected through a random sampling technique using a 5-point Likert scale structured questionnaire ranging from "strongly disagree to strongly agree". The data was collected from October 14, 2025, to April 10, 2026. The target population was 226, consisting of Fintech and Banking experts working in the Fintech Industry across India.

Table 1: Demographic Profile Of The Participants

		n	%
Gender	Women	27	11.9
	Man	199	88.1

Age	18-25	41	18.1
	26-55	185	81.9
Industry	Fintech	226	100.0
Fintech Industry Sector	Paytech	102	45.1
	Wealth Tech	37	16.4
	Insurtech	22	9.7
	Lendtech	65	28.8
Occupation	Technology	90	39.8
	Top Management	39	17.3
	Banking	51	22.6
	Financial Services	46	20.4
Country	India	226	100.0

Out of 226 respondents, 88.1% are males while 11.9% are females. On classifying the respondents based on age, the distribution is 18% in the 18-25 years of age group, while 88% are in the age group of 26 to 55 years. The sector-based classification of respondents is 45% pay tech, 28.8% lend tech, 16.4% wealth tech, and 9.7% Insurtech.

The occupation-based classification of them are 39.8% technology-related, 22.6% banking-related, 20.4% financial services related while 17.3% are from top management of financial institutions.

3.2 Measurement of Constructs

The construct "Fintech Success Drivers" was measured using indicators connected to regulatory framework, cybersecurity, collaboration among institutions, government initiatives, infrastructure, policy reforms, talent development, risk mitigation, and fintech performance tracking. "Implementation of Fintech" was measured as a single-item construct reflecting the extent of fintech implementation practices, while "Performance" was measured using indicators related to earnings and organisational growth.

3.3 Data Analysis Technique

The empirical data were examined using Partial Least Squares-Structural Equation Modelling (PLS-SEM). PLS-SEM was considered suitable for the analysis because of its predictive direction and its fitness for analysing complex relationships among latent constructs. The analysis was carried out using the packages seminr, cSEM, readxl, and dplyr. The seminr and cSEM packages were primarily used for structural equation modelling and model assessment, while readxl was used for importing the dataset and dplyr was employed for data handling and preprocessing.

The assessment is completed in two stages: measurement model assessment, followed by structural model assessment. The measurement model assessment includes parameters such as indicator reliability, internal consistency reliability, convergent validity, discriminant validity, & collinearity assessment. Additionally, the structural model was assessed using path coefficients, coefficient of determination (R^2), predictive relevance (Q^2), effect size (f^2), and bootstrapping methods to examine the significance and robustness of the proposed relationships.

A bootstrapping procedure for 5,000 random resamples was performed to determine the significance of the structural paths and to form confidence intervals for hypothesis testing.

IV. Hypothesis Development

The success of implementing fintech depends on identifying and leveraging Fintech success drivers that bring economic growth and enhance performance in financial institutions. The paper is based on the following hypothesis:

$H_0 1$: Fintech Success drivers do not influence the Implementation of Fintech.

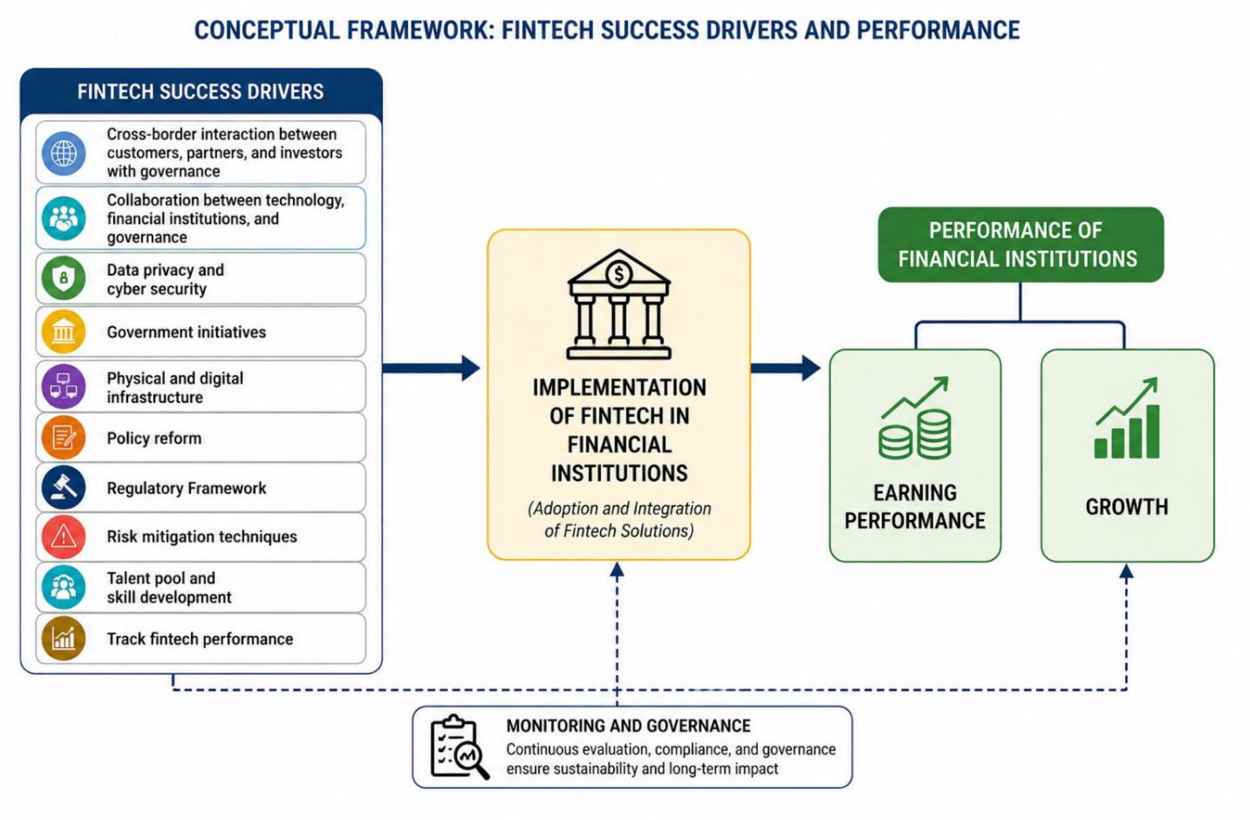
$H_1 1$: Fintech Success drivers influence the Implementation of Fintech.

$H_0 2$: Implementation of Fintech does not influence the performance of Financial Institutions

$H_1 2$: Implementation of Fintech Influence Performance of Financial Institutions

$H_0 3$: Fintech Success drivers do not influence the Performance of Financial Institutions

$H_1 3$: Fintech Success drivers influence the Performance of Financial Institutions.



V. Result And Finding

5.1 Confirmatory Component Analysis (Cca)

CCA is a standard method in PLS-SEM widely applied to examine the adequacy of latent constructs and ensure that the indicators appropriately represent them (Schuberth et al., 2018). With this view, CCA is applied to our proposed measurement model within the PLS-SEM framework using R software for analyzing the robustness and validity of the constructs used in the study. The reflective measurement model is broadly examined using indicators loading, internal consistency, reliability, convergent validity and discriminant validity. Outer loadings estimates were evaluated to validate the indicator's reliability whereas Cronbach's alpha, composite reliability and rhoA were computed to verify internal consistency. Further, Average Variance Extracted (AVE) values were employed to conform convergent validity. In addition, discriminant validity was examined using HTMT approach to ensure empirical distinctions among the constructs of the study. Collectively, these measures demonstrate whether the measurement model satisfies the threshold set in PLS-SEM (Hair et al., 2020).

Table 2: Indicator Loading and Significance

Indicator Loading and Significance	Outer loading	Bootstrapped loading	T statistic	p value
Collaboration between technology, financial institutions, and governance <- Fintech Success	0.7700376	0.770	13.943	0.001
Cross-border interaction between customers, partners, and investors with governance <- Fintech Success	0.6506695	0.651	7.176	0.007
Data privacy and cyber security <- Fintech Success	0.8178603	0.810	14.194	0.000
Earning <- Performance	0.8800524	0.880	30.929	0.000
Government initiatives <- Fintech Success	0.7530598	0.747	13.567	0.002
Growth <- Performance	0.8243091	0.820	17.484	0.000
Physical and digital infrastructure <- Fintech Success	0.7634799	0.760	13.259	0.002
Policy reform <- Fintech Success	0.7344133	0.719	9.679	0.001
Regulatory Framework <- Fintech Success	0.7685590	0.754	10.116	0.003
Risk mitigation techniques <- Fintech Success	0.7200063	0.708	8.943	0.004
Talent pool and skill development <- Fintech Success	0.8111423	0.803	15.428	0.002
Track fintech performance <- Fintech Success	0.7019697	0.697	11.281	0.002

Higher outer loading value ensures that the indicators adequately explain the variability of the construct and contribute significantly to its measurement. In general, outer loading values above 0.70 are accepted to be satisfactory. To examine the statistical relevance and stability of the indicator loadings, we perform a non-parametric bootstrapping procedure. The obtained indicator loadings, bootstrapped estimates, associated t statistic and p-values are listed in Table 2. The result demonstrates that all indicators load above the recommended threshold except Cross-border interaction between customers, partners, and investors with governance for which loading still remain above 0.6, the minimum acceptable threshold. Among the indicators of Fintech success drivers, "Data privacy and cyber security" (0.8178603) and "Talent Pool and skill development" (0.8111423) contributed the most, indicating their strong relevance to Fintech success. A similar trend was observed for the indicators of construct "Performance", namely Earning (0.8800524) and Growth (0.8243091) which demonstrated adequate representation of organizational performance. Further, the bootstrapping results confirmed the statistical significance of all the indicators considering the obtained p-values less than 0.05, as presented in Table 2 [37].

Table 3: Construct Reliability and Convergent Validity

	Composite reliability (rho_c)	**Average variance extracted (AVE)**
Fintech Success	0.928	0.563
Implementation	1.000	1.000
Performance	0.842	0.727

Table 3 illustrates the reliability and convergent validity results for the model constructs. Composite reliability determines the internal consistency among construct indicators, whereas AVE evaluates the proportion of variance obtained by the construct relative to its indicators. A value more than 0.70 for composite reliability and 0.50 for AVE are considered satisfactory, thereby confirming the adequacy of the measurement framework [38]. The statistical findings in Table 3 provide empirical evidence for the reliability and convergent validity of the constructs in the framework. In particular, the construct "Fintech success drivers" demonstrated strong reliability with a composite reliability value of 0.928 and adequate convergent validity with an AVE value of 0.563, while the Performance construct also demonstrated robust reliability and convergent validity.

Table 4: Discriminant Validity

Discriminant Validity	**Heterotrait-monotrait ratio (HTMT)**
Implementation of Fintech <-> Fintech Success	0.232
Performance <-> Fintech Success	0.296
Performance <-> Implementation of Fintech	0.586

To establish discriminant validity, the Heterotrait-Monotrait ratio (HTMT) was computed, and values less than 0.85 indicate satisfactory discriminant validity among constructs [39]. As presented in Table 4, the obtained HTMT results suggest strong discriminant validity and confirm that the constructs in the model are sufficiently distinct from each other.

Table 5: Nomological Validity

Model Fit	**Saturated model**	**Estimated model**
SRMR	0.1299881	0.1312653
Squared Euclidean distance (d_ULS)	1.537618	1.567983
Geodesic distance (d_G)	0.5497715	0.5538368
Chi-square	592.6307	587.621

NFI	0.6337223	0.6368186

In PLS-SEM, nomological validity assesses the consistency of hypothesised relationships among constructs obtained by empirical study with the theoretical framework. The fit indices, including SRMR, d_ULS, d_G, Chi-square and NFI were used to determine how closely the theoretical model corresponds with the covariance structure observed in the dataset. Table 5 represents the obtained values of the above measures for both saturated and estimated models.

The SRMR values obtained for both models are closely comparable, indicating consistency between the structural model and observed data. Although the values exceed the threshold of 0.08, they remain within an acceptable range within the context of exploratory research. The squared Euclidean distance (d_ULS) and Geodesic distance (d_G) values were observed to be relatively close, suggesting minimal discrepancy between the empirical and the model-implied covariance matrices. Note that Chi-square values are highly sensitive to sample size and model complexity, thereby contributing to the relatively high values reported in Table 5. The NFI values of the saturated and estimated models are below the threshold limit of 0.9, suggesting a moderate level of model fit considering the newly developed constructs of our exploratory study [40], [41]. Therefore, the overall model fit was evaluated using multiple fit indices, collectively suggesting reasonable model adequacy and providing sufficient empirical support for the proposed conceptual framework

Table 6: Predictive Validity

Correlation	**Fintech Success**	**Implementation**	**Performance**
Fintech Success	1.0000000	0.2431772	0.2302234
Implementation of Fintech	0.2431772	1.0000000	0.4660827
Performance	0.2302234	0.4660827	1.0000000

The correlation matrix among the constructs is given in Table 6 reflects the direction and strength of relationships between them within the proposed conceptual framework. Note that higher correlation coefficients close to +1 suggests strong positive association and enhanced predictive relevance while its lower value indicate the less predictive outcome of the model [42]. Positive values in the table illustrates that the constructs move in same direction with high values reflecting strong association between the variables. In particular, stronger Fintech related enabling factors are associated with improved Fintech implementation. Similarly, it is observed that favorable Fintech success drivers contribute positively to organizational performance outcomes. Further, the strongest predictive power among all was noted between Implementation of Fintech and Performance which demonstrates that improved implementation practices are associated with higher organizational growth and earnings. Thus, the result provides preliminary empirical support for the presumed theoretical relationships within the model. In conclusion, the structural model analysis may be carried out as the measurement model resulted to be reliable.

5.2 Structural Model & Its Assessment

The structural model assessment in PLS-SEM is widely applied to analyse complex models involving multiple constructs with an aim to examine the predictive & explanatory power of the proposed model with the use of indicators such as collinearity statistics, R^2 values, Q^2 values, effect sizes and bootstrapped path coefficients [38].

Table 7 Collinearity Statistics

Collinearity Statistics	VIF
Collaboration between technology, financial institutions, and governance	2.445914
Cross-border interaction between customers, partners, and investors with governance	2.207604
Data privacy and cyber security	3.508948
Earning	1.263381
Government initiatives	2.512496
Growth	1.263381
Implementation of Fintech	1.000
Physical and digital infrastructure	2.658962
Policy reform	2.132205
Regulatory Framework	3.306290
Risk mitigation techniques	2.436600
Talent pool and skill development	2.953050
Track fintech performance	1.878733

Table 7 presents the collinearity assessment of the indicators using Variance Inflation Factor (VIF). The objective of collinearity assessment is to assess whether strong correlations among construct indicators distort the estimation of path coefficients and affect the stability of the structural model. VIF, as a collinearity assessment, measures the inflated variance of an indicator variable due to correlation with other variables. It is recommended that VIF values should be less than 5.0 to confirm the absence of critical multicollinearity issues, while values strictly less than 3.3 are often treated as ideal [43]. From Table 7, it can be concluded that all VIF values fall within acceptable threshold limits and multicollinearity concern is not significant in our model, suggesting that the indicators contribute independently. Thus, the collinearity statistics validate the stability as well as reliability of the model estimates.

Table 8 R Square

	R-square	R-square adjusted
Implementation of Fintech	0.0642	0.0600
Performance	0.3644	0.3587

Table 8 consists of R^2, the coefficient of determination and its adjusted values for the endogenous constructs. The above R^2 values describes the ratio of variance in the construct determined by its predictors, thereby indicating the model's explanatory strength. The adjusted R^2 values further refined this calculation by considering the number of predictors studied in the model and the sample size. R^2 and adjusted R^2 values lie in [0,1], where values nearer to 1 signify higher explanatory power of the structural model (Ozili, 2023).

The result reflects that the proposed model explains 6.42% of variance in Implementation of Fintech suggesting that success drivers exert a relatively modest explanatory influence on Fintech implementation. Although the

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explanatory effect is limited, such values are acceptable in exploratory studies involving technology adoption constructs where multiple external factors may influence implementation practices. Further, the model was able to explain about 36.44% of variance in Performance, indicating a moderate explanatory power. Based on the data, the findings suggests that Fintech success drivers and Implementation of Fintech are meaningful contributor towards explaining organizational performance outcomes. Moreover, R^2 and adjusted R^2 values are observed to be relatively closer which demonstrate model stability and suggest that the included indicators do not inflate the explanatory power of the model. In conclusion, the model possesses acceptable explanatory power, particularly in explaining organizational performance within the Fintech implementation framework.

Table 9: F-Square

	f-square
Fintech Success -> Implementation of Fintech	0.063
Implementation of Fintech -> Performance	0.229

The F^2 statistic in PLS-SEM assesses the relative impact of an exogenous variable on an endogenous variable by examining the reduction in the endogenous construct's R^2 after excluding the predictor from the structural model. According to Jacob Cohen (1988), F^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effect sizes, respectively.

Table 9 provides the effect size F^2 values for the structural relationships in the model. The result suggests that Fintech success drivers have a small effect size on Fintech implementation. In other words, Fintech success drivers exert a relatively limited but meaningful contribution towards explaining the Implementation of Fintech practices. Further, Implementation of Fintech exerted a moderate effect on Performance, as reflected by the obtained F^2 value of 0.229. Overall, the structural model exhibits practically meaningful relationships, particularly regarding the influence of Fintech Implementation on organisational performance.

Table 10: Predictive Relevance Q-square

	Q²predict	**RMSE**	**MAE**	
Implementation of Fintech	0.032	1.007	0.656	
Performance	0.039	1.008	0.713	

The Q^2 statistic is an important tool in PLS-SEM that serves as an indicator of predictive relevance, evaluating the structural model's capability by analysing the degree of accuracy in predicting omitted data points. Predictive relevance of the model is established when the Q^2 value for an endogenous construct exceeds zero. However, the model has moderate predictive relevance for Q^2 values in [0.25,0.5] and values above 0.50 represent substantial predictive relevance (Shmueli et al., 2016, 2019). Table 10 shows the Q^2 predictive results along with Mean Absolute Error (MAE) & Root Mean Square Error (RMSE) values for the endogenous model constructs. The outcomes confirm that both of the endogenous constructs reported positive Q^2 values. Thus, the structural model possesses predictive relevance and demonstrates the ability to predict the endogenous constructs within the proposed framework. Further, MAE & RMSE values furnish information regarding predictive error, where higher values indicate less predictive accuracy of the model. The empirical values in the table suggest a reasonable level of prediction accuracy within the model. Collectively, the proposed structural model possesses acceptable predictive capability and relevance in explaining Fintech implementation and organisational performance outcomes.

5.3 Methodological Robustness Validation

The study conducted primary research to investigate the relationship between Fintech success and its performance, considering successful implementation of Fintech in the Indian context. Methodological concerns associated with survey research need to be addressed, including endogeneity, common method bias (CMB), single-source bias, and the limitations of cross-sectional studies [44], [45].

Table 11: Gaussian Copula Test for Endogeneity

Path	Original Path Coefficient	Copula Term Coefficient	p-value (Copula)	Endogeneity Issue
Fintech Success -> Performance	0.367	-0.100	0.688	No
Performance -> Implementation of Fintech	0.697	-0.309	0.140	No

Table 11 shows that the Gaussian copula tests for the predictors are statistically insignificant ($p > 0.05$), indicating that the relationships of structural paths are not biased due to endogeneity. The findings confirms that the relationships between model constructs are robust, not for unobserved confounding variables.

The Gaussian Copula approach addresses the endogeneity issue [46], [47]. The approach is suitable for the PLS-SEM approach and not required for instrumental variables. The results suggest that endogeneity is not a problem as none of the copula terms are statistically significant ($p > 0.05$) in the structural path model

Common method bias is applied within the procedural, such as anonymous data collection, clear-worded items, inclusion and exclusion criteria, and separation of measurement items. Additionally, a collinearity assessment is conducted Kock (2015), which suggests that all variance inflation factor (VIF) values are below and near 3.3 (Table 7), showing that CMB is not a concern in the result.

Although data collection was confined to a single source of information, efforts were made to minimise the mono-method bias through expert review and pilot testing of the questionnaire. The study acknowledges the temporal limitations of a cross-sectional study and encourages forthcoming research to collect longitudinal data to review causal relationships with time-lagged effects better.

5.4 Hypothesis Result And Interpretation

The structural relationships among the construct were tested using a bootstrapping technique with 5000 resamples in PLS-SEM of R software. The relevance of the hypothesized relationships was examined through path coefficients (β), t-statistics, p-values, and bootstrapped confidence intervals. The significant threshold limit of the p-value is 0.05 [37].

Table 12: Structural Model Robustness

Hypothesis	Structural Path	Original sample (β)	Sample mean (M)	Standard deviation (STDEV)	t-statistics	p-values	95%CI	Result

H1	Fintech Success Drivers -> Implementation of Fintech	0.243	0.255	0.080	3.027	0.014	(0.098,0.403)	Supported
H2	Implementation of Fintech-> Performance	0.436	0.434	0.086	5.078	0.000	(0.255,0.590)	Supported
H3	Fintech Success -> Performance	0.124	0.129	0.085	1.454	0.133	(-0.046,0.293)	Not Supported

The results interpreted from Table 12 reveal that Fintech success drivers exert a statistically significant influence on the Implementation of Fintech, thereby supporting $H_{1}1$. This establishes that favourable Fintech success drivers, including regulatory support, cybersecurity, collaboration, infrastructure, and policy reforms, contribute positively towards Fintech Implementation practices. Similarly, it is observed that effective Fintech implementation significantly enhances organisational performance outcomes, supporting $H_{1}2$. However, the direct relationship between Fintech success drivers and Performance was not statistically significant as can be seen from the high p-value of 0.133. Moreover, the confidence interval included zero, which suggest $H_{1}3$ was not supported [49]. Therefore, Fintech success drivers do not have a direct significant influence on organisational performance.

In conclusion, the study involved developing and validating novel constructs related to the success of Fintech implementation. Accordingly, Confirmatory Composite Analysis (CCA) was performed to test the measurement model. The robustness of the structural model is confirmed using bootstrapping with 5,000 resamples and the model demonstrated acceptable predictive relevance, with positive Q^2 values (Table 10). The obtained results demonstrate empirical rigour and robustness, despite the use of newly constructed measures in primary research.

Table 13: Total Effect Assessment

Structural Path	**Total Effect (β)**	**95% Confidence Interval**	**Interpretation**
Fintech Success Drivers-> Performance	0.230	(0.081, 0.390)	Significant positive total effect

Table 13 presents the total effect evaluation of the structural model. Total effect analysis explores the overall influence of a construct on another by considering direct & indirect relationships within the model. The result suggests that Fintech success drivers have a positive & statistically significant overall effect on Performance. Although the direct relationship between Fintech success drivers and Performance was insignificant in the model assessment, the significant total effect indicates that the influence occurs indirectly through the Implementation of Fintech.

The combined result demonstrates that favourable Fintech success drivers, such as regulatory support, infrastructure, collaboration, and cybersecurity, contribute to improved organisational performance mainly by strengthening Fintech implementation practices. The results emphasise the significance of Performance as a mediating factor in the fintech success implementation model for fintech growth in the Indian economy.

VI. Discussions

The development and growth of fintech, addressing implementation challenges by considering fintech success drivers, is vital for the economic progress of developing countries like India. The study explores and confirms the fintech success drivers that enable the effective implementation of fintech and drive performance outcomes. The DOI–RBV implementation considers the relationship between Fintech success drivers, implementation of fintech and performance. Studies reveal that Fintech success drivers positively influence implementation. Collaboration between technology, financial institutions, and governance; cross-border interaction between customers; data privacy and cybersecurity; government initiatives; physical and digital infrastructure; policy reform; Regulatory Frameworks; risk mitigation techniques; talent pool and skill development; and tracking fintech performance are crucial for fintech implementation. Moreover, the study highlights that performance, measured through earnings and growth, is impacted by the implementation of fintech.

The practical insights have significant implications for policymakers and regulators in designing fintech implementation frameworks for financial institutions to prioritise Fintech success drivers for long-term profitability and growth.

6.1 Theoretical And Practical Implication

The study extends DOI by incorporating Fintech-specific external forces such as cross-border partnerships, government initiatives, policy reforms, and data privacy regulations. The DOI goes beyond consumer adoption by embedding regulatory and ecosystem factors directly into the diffusion process, making it more relevant to financial institutions. Second, RBV is expanded by introducing Fintech-specific internal capabilities, including cybersecurity, digital infrastructure, risk mitigation, and talent development. The resources represent strategic competencies that strengthen performance and successful implementation. Empirical validation using PLS-SEM and CCA further reinforces the theoretical contribution that enhances the credibility for future academic research.

The findings contribute actionable inferences for industry stakeholders, such as policymakers, to take initiatives on regulations and infrastructure that will support the successful implementation of fintech. Fintech firms, banks, and traditional institutions may prioritise key factors such as governance, collaboration, cybersecurity readiness, and talent development to build sustainable growth.

6.2 Limitation

Despite the contributions, the study focuses on financial institutions, which may confine the generalisation of outcomes to other sectors adopting FinTech. This study is conducted within India; the results require careful analysis before its directly application to the global arena with different regulatory, technological, and economic environments.

7. Conclusions

Although India has a high fintech adoption rate of nearly 87%, the industry continues to face significant challenges in implementing fintech solutions. The study integrates the Diffusion of Innovation (DOI) and the Resource-Based View (RBV) to assess the success of fintech implementation in a developing economy. The study explores and confirms a set of Fintech industry-specific success drivers, including collaboration between technology, financial institutions, and governance; Cross-border interaction between customers; Data privacy and cybersecurity; Government initiatives; Physical and digital infrastructure; Policy reform; Regulatory Framework; Risk mitigation techniques; Talent pool and skill development; and tracking fintech performance. The results emphasise the need for industry stakeholders to strengthen internal capabilities while leveraging external diffusion innovation forces to achieve profitability and sustainable growth. The study advances theory by integrating the DOI & RBV with industry-specific fintech success drivers, which may be used for both academic research and practical applications. The study provides a strategic implementation roadmap for policymakers, regulators, and practitioners, highlighting the importance of policy reform, infrastructure development, and skill enhancement for overcoming implementation challenges. The integration of fintech success drivers and implementation provides both theoretical and practical implications for scaling fintech innovation not only in India but also in emerging markets seeking sustainable financial transformation.

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