Augmenting Bank Credit Flow to Agro-Processing SMEs through Financial Technology (FinTech): Evidence from Tanzania

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Abstract: -The drivers of bank credit flow of transaction costs, credit risk management, information asymmetry, and institutional lending structure are extensively examined. Previous studies have assessed how SMEs might address their financing issues from a demand side. This study is inclined toward the supply side of financing. We aimed to determine how FinTech can counteract the effects of lending costs, information asymmetry, and credit risk management to influence the flow of bank credit to agro-processing SMEs and other entrepreneurs. A total of 399 questionnaires were collected for statistical analysis using partial least square structural equation modeling (Smart PLS). We demonstrate that FinTech as a moderator reduces the negative effects of information asymmetry and credit risk management to allow agro-processing SMEs to obtain more loans. Policymakers can use the findings of this study to improve banks' financial technology in lending activities for the sustainability of entrepreneurial activities.

Key- Words: - Financial technology, FinTech; Information Asymmetry, Agro-processing SMEs, Credit flow, Credit Risk management, institutional lending structures, commercial banks.

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1 Introduction

Tanzania has identified agro-processing SMEs (Ap-SMEs) as the cornerstone of transforming an economy from an agricultural-based to an industrial-based economy. With 65.31% of its people employed in agriculture, the agro-processing industry is the best-prospect sector designated by the country as the icon of the industrial economy by 2025, [1]. Globally, Ap-SMEs are essential for generating income and creating jobs, especially in underdeveloped countries, Tanzania included. Trade credit and loans from commercial banks are SMEs' primary funding sources. According to a vast body of research, banks are the main source of loan funding for SMEs in both developed and developing nations, [2], [3], [4], but often, SMEs struggle to secure loans from them. Due to the credit gap between SMEs and commercial banks, credit availability to SMEs has attracted the focus of most researchers. Despite several attempts to address this issue, the results have been conflicting and inconclusive. In [5] and [6] state that the below factors frequently prevent SMEs from obtaining bank credit: their informality, SMEs' opaqueness, the conditions imposed by lenders, ineffective financial technology for loan processing, and a lack of collateral to offer loan insurance. Our study looks at how bank financial technology (FinTech) impacts credit availability for small- and medium-sized enterprises (SMEs) engaged in agro-processing in Tanzania. Due to flaws in the credit market, such as high loan costs, information asymmetry, credit risk, and unpleasant bank lending structures, small and medium-sized firms (SMEs) typically experience bank financing constraints, [7]. Banks have adopted new business models in response to the recent ten-year technological acceleration to serve customers better and increase process effectiveness, [8]. The financial sector is undergoing a global transformation due to technological advancements like artificial intelligence, blockchain, cloud computing, big data analytics, and the internet of things. FinTech's fast growth is generating much academic interest. Many studies have appreciated FinTech's rise, suggesting that newer technologies can dramatically revolutionize financial services by making transactions more affordable, convenient, and secure, [9], [10].

The drivers of bank credit flow are examined in this study to see if FinTech might play a moderating influence on the supply side. We want to see if fintech can help Ap-SMEs overcome impediments to credit, such as bank lending costs, information asymmetry, and credit risk management. The study examines whether FinTech can broaden financial intermediation theory and act as a reliable, secure, and quick solution for increasing loans to Ap-SMEs. Most of the research mentioned above focuses on the effects of outside FinTech, although certain publications, [11], [12], examine the influence of FinTech on the banking industry. We are unaware of any research exploring the role of bank FinTech as a mediator in increasing loans to Ap-SMEs. Therefore, our study focuses on filling this academic gap because fintech simplifies and smoothens service offerings. Specifically, it will add to the current body of knowledge in which fintech is often applied in providing other banking services compared to loan offerings. We suggest that bank FinTech impacts loan flow in three ways: First, it mitigates information asymmetry by using big data analytics to capture borrowers' information in 360 degrees, preventing banks from avoiding SME financing due to their opaqueness. Second, FinTech reduces credit risk by enhancing bank internal governance and controls, which increases lending appetite among small businesses. Finally, bank FinTech can potentially expand bank loans to Ap-SMEs and other small businesses by reducing lending costs.

2 Literature Review and Hypotheses Development

2.1 Theoretical Underpinnings of the Study

Agro-processing SMEs are enterprises converting agricultural produce from agriculture to final products with capital in machinery not exceeding TZS 800 million and with employees from 1 and not exceeding 99, [13]. The agro-processing sector is an inevitable means of economic development via increasing employment and improving agricultural productivity as the sector strongly links all industries, from the extraction of raw materials to the tertiary sector. On the other side, we use Cheng's concept to define bank financial technology. Bank FinTech refers to applying emerging technologies in the financial industry, such as artificial intelligence, blockchain, cloud computing, big data, and internet technology, [14]. Tanzania's fintech sector has grown fast in the recent ten years. Fintech services were initially limited to airtime purchases, money transfers, and cash deposits and withdrawals. Fintech companies in Tanzania have facilitated banks to offer various services based on data and financial technologies, such as remittances, digital savings, digital lending, and microinsurance. The launch of government policies and efforts focusing on information and communication technology is favorably connected with regulatory reforms in the payment sector and the transformation in the fintech start-up scene (ICT). This study uses the financial intermediation theory because it aims to justify the motivations for banks adopting alternative banking channels. The financial intermediation theory concentrates on the transaction cost theory and information asymmetry by examining the existence of financial intermediaries and how they can supply financial services, including bank credit, [15], [16], [17], [7]. Fintech's entry is considered to broaden the financial intermediation theory, boosting financial intermediaries' potential to achieve long-term growth, liquidity maintenance, and sustainability.

2.2 Bank Transaction Costs

Transaction costs (TC) are the total direct and indirect costs incurred by banks when extending loans to SMEs, including travel time and costs, local authority and lawyer fees, meeting facilitation, business viability measuring costs, security evaluation, contract breaching costs (case filing fees, debt collectors hiring fees), and other fees, [18]. Researchers generally agree that transaction costs increase lending rates, lower loan amounts by subtracting administrative costs, and occasionally lead lenders to deny credit applications, [19], [20]. However, based on [14], recent modernization in the banking sector has reportedly reduced transaction costs to the extent that banks no longer have a reason to limit loans to SMEs. This study reasonably investigates the implications of transaction costs in agro-processing in a developing country like Tanzania. It is expected that high transaction costs on the banks' side limit bank credit flow to Ap-SMEs, and as such, it is hypothesized that:

Hypothesis 1 (H1). Transaction costs have a direct and negative effect on the flow of bank credit to Ap-SMEs

2.3 Information Asymmetry

Asymmetry between banks and SMEs refers to a gap or mismatch in information [21]. Information asymmetry negatively and significantly influences bank credit flow from the lender's side, [22]. Even though bank credit is widely regarded as the most essential and comprehensive external source of SME financing, SMEs have been left unfunded due to information gaps.

Other works of literature, such as, [14] and [9], argue that the information asymmetry problem is dwindling due to technological developments in the banking industry. Financial and technological improvements, such as electronic banking, big data and big data analytics, and credit reference bureaus, have made it easier for bankers to get the information needed to provide loans to SMEs. According to this study, if bankers have all essential information on Ap-SMEs, credit supply will likely increase because banks prefer to approve loans to SMEs with more transparent information and the contrary will limit the flow of loans from them. Based on this fact, this study predicts that:

Hypothesis 2 (H2). Information asymmetry directly and negatively affects the flow of bank credit to Ap-SMEs.

2.4 Credit Risk Management

[15] defines credit risk management (CRM) as a collection of integrated duties and actions for regulating and directing credit risks encountered by commercial banks. It is important to remember that risk management processes are not meant to eliminate risks; instead, they are meant to manage the possibilities and threats that can lead to risk. Research, [2], found that in Egypt, risk management has a detrimental impact on bank credit supply to SMEs and other borrowers in general. Their results are congruent with the financial intermediation theory.

Most SMEs' credit risk management has limited the number of bank loans they have received, as most banks avoid lending to SMEs due to the danger of default. The bank's opinion of a significant risk of default in SMEs is reflected in high lending rates and the introduction of stringent collateral requirements. According to [23] the requirement for collateral looked like a substantial barrier to SME financing because banks saw it as a risk buffer. Most SMEs cite the lack of collateral as a primary reason for banks' rejection of their loan proposals. Plenty of empirical studies, [24], [25], show a significant relationship between collateral and borrowers' risk. Before extending loans, commercial banks use a variety of credit risk evaluations. Because most SMEs do not qualify for loans, the assessments have had a detrimental impact on their credit flow. Based on this fact, this study predicts that:

Hypothesis 3 (H3). Credit risk management has a direct and negative effect on the flow of bank credit to Ap-SMEs

2.5 Institutional Lending Structure

Studies of bank credit, [26], [27], found that institutional lending structure, such as a bank's lending culture, credit rules, lending principles, and procedures, has a considerable beneficial impact on bank credit supply. In [28] argues that variations in credit regulations, bank organizational structures, credit staff training, internal banking policies, the upward recommendation system, authorization limits, and head office instructions all impact the flow of credit to SMEs.

The supply side of credit has been one of the critical reasons for SMEs' credit constraints to a greater extent. According to [26], lenders cause credit constraints in three ways: (1) prospective SMEs may not apply for credit because they are discouraged by a particular bank's available processes and criteria; (2) SMEs can be declined due to a particular bank's credit risk assessments; and (3) accepted SMEs may receive unfavorable credit terms as expected. Banks have consistently marginalized SME sectors in their lending strategies in certain conditions. The AP-SMEs will take control if the agro-processing industry is given priority in the banking policies and guidelines. Therefore, the study hypothesizes that:

Hypothesis 4 (H4). The institutional lending structure has a direct and positive effect on the flow of bank credit to Ap-SMEs.

2.6 Financial Technology (FinTech) as a Moderator

FinTech applications such as internet information technology, big data, blockchain technology, and artificial intelligence, according to [29] are being used to provide SME loans. Various professions have recently scrutinized the evolution of financial technology and in the financing sector, FinTech has propelled the supply of finance to SMEs to new heights, [14], [30], [9]. FinTech impacts banks' ability to manage SMEs' credit risks. Because commercial banks only have limited time to investigate and evaluate loans, bank financial technology has improved business models that have increased bank loans. FinTech decreases the number of both bank and SME visits during the lending procedure. Banks are more willing to lend to small and medium-sized businesses, [31].

Furthermore, because FinTech requires less documentation, fewer workers, and fewer physical branches, banks' loan revenues increase as transaction costs decrease, [32]. By allowing potential borrowers to do much of the work themselves, e-banking technology, for example, can substantially reduce the time it takes to complete loans. As a result of the lower transaction costs associated with FinTech, providing e-lending services to SMEs allows banks to expand their business. In [33], FinTech is expected to help banks improve credit information availability and accuracy, increase the number of information access channels and sources, and bridge the information gap between banks and small businesses. The introduction of FinTech has resulted in more information exchange among credit market participants. Sharing data with other banks' extensive databases could reduce the cost of locating potential borrowers and credit risk. The introduction of FinTech has resulted in more information interchange in the credit market. Sharing data with other banks' large databases might lower the cost of finding potential borrowers while lowering credit risk. As a result, the following four hypotheses are proposed in this study:

Hypothesis 5 (H5). Financial technology (FinTech) has a direct and positive effect on the flow of bank credit to Ap-SMEs

Hypothesis 6 (H6). Financial technology positively moderates transaction costs to increase Ap-SMEs' bank credit flow.

Hypothesis 7 (H7). Financial technology positively moderates information asymmetry to increase bank credit flow to Ap-SMEs.

Hypothesis 8 (H8). Financial technology positively moderates credit risk to increase bank credit flow to Ap-SMEs.

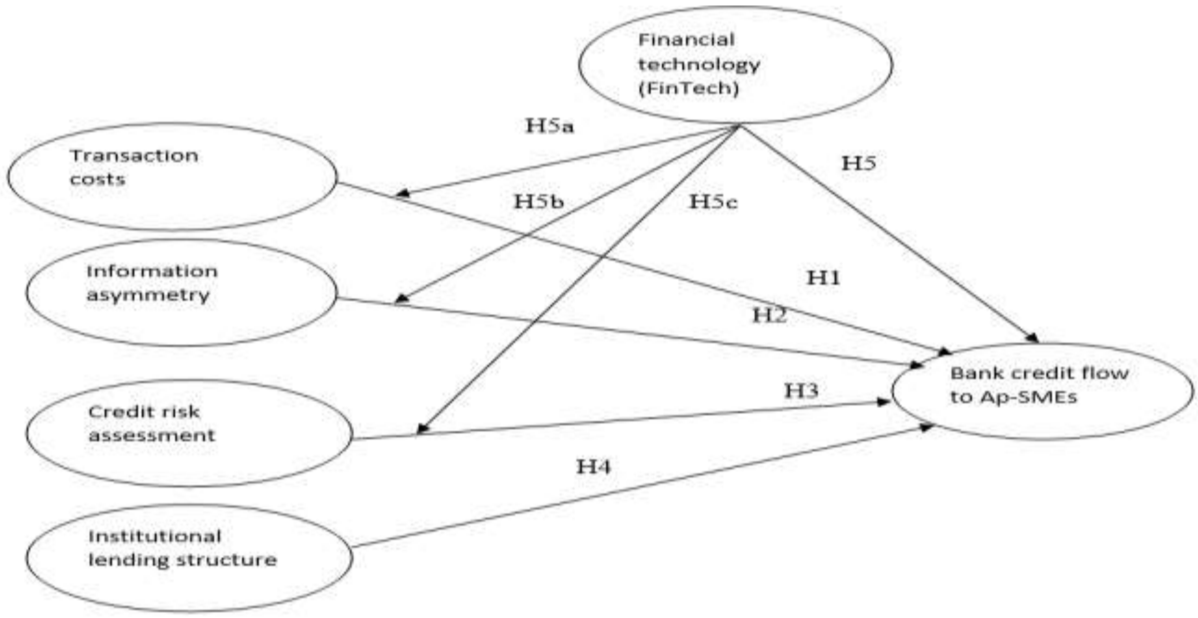

Fig. 1: The proposed research model

3 Research Methodology

3.1 Sampling Method

This study used a quantitative technique to ascertain the relationships between the researched constructs to provide precise and reliable results. A questionnaire was distributed to lending officers at commercial banks using both the drop-off and pick-up techniques and the online questionnaire. The loan experts contacted included branch managers, credit officers, credit analysts, and relationship managers. Since it was difficult to gather data from the entire population due to the abundance and widespread dispersion of bank branches across the nation, sampling was done to determine the sample size. 397 bank branches were used as the sample size for this study by the researchers. Since the study population met the requirements of the Yamane formula, the sample size was established using that formula, [34]. The questionnaire was therefore given out to 484 respondents to address the problem of a low response rate.

A multi-stage cluster sampling technique was also used to choose the research sample. By segmenting Tanzania into zones, regions, and eventually cities, the multi-stage cluster sampling technique, which has greater statistical efficiency and is simpler to carry out, ensured that the intended respondent was reached. The cities were also picked because they are commercial hubs and are concentrated with many banks and agro-processing SMEs, [35]. The participant was selected using the purposive sampling strategy based on their seniority and credit-related experience because just one respondent from each bank branch was necessary to complete the survey, [36]. Finally, only 401 of the 484 issued questionnaires were returned. Two (2) questionnaires were rejected because at least 10% of their variables had missing data, [37], [38]. 399 acceptable sets are retained, equivalent to 82.4% of the response rate

3.2 Instrument Development

The items in the questionnaire were mostly modified from previous empirical research, which was then validated through a detailed analysis. Sections A and B of the self-administered questionnaire were created. Section A was used for profiling, and Section B measured different constructs. The questions to measure bank credit flow were taken from [39] and [40], transaction costs from [19] and [41] information asymmetry from [20] institutional structure from [42] and financial technology items from [43] and [44]. Section B items were scored on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (strongly agree).

3.3 Demographic Characteristics of Respondents

The respondents' profiles are summarized in Table 1. Approximately 79.5% of lending officers have four years of experience in the banking industry. This represents the lending experience and skill of the respondents. According to statistics, 72.2% of banks have set up agro-processing SME units. This could indicate that Ap-SMEs' funding is a priority in Tanzanian banks. Most of the banks, about 64.4%, have been in business in Tanzania for over 15 years. This likely demonstrates their familiarity with the Tanzanian SMEs financing sector. Furthermore, the experience of these banks may explain why most of them, 61.7%, have more than 20 locations spread around the country.

Table 1. Demographic statistics

Demographic	Category	Frequency	Percentage (%)
Position of respondent	Branch Manager	63	15.8
	Credit Manager	63	15.8
	Credit Officer/Analyst	174	43.6
	Relationship Manager	99	24.8
Experience of respondent	0 year – 3 years	82	20.6
	4 years – 6 years	132	33.1
	7 years – 10 years	128	32.1
	11 years and above	57	14.3
Bank's age in Tanzania	0 – 5 years	16	4
	6 -10 years	51	12.8
	11 – 15 years	75	18.8
	Above 15 years	257	64.4
Bank's branch number	0 – 10 branches	58	14.5

	11 – 20 branches	95	23.8
	21 – 30 branches	37	9.3
	31 – 40 branches	35	8.8
	41 – 50 branches	36	9.0
	Above 51 branches	138	34.6
Banks with agro-processing SMEs unit	Yes	287	72.2
	No	111	27.8

4 Analysis of Data

4.1 Measurement Model

Smart PLS software Version 3 was used to investigate the research hypotheses and model. Convergent validity, discriminant validity, and reliability of each construct were confirmed in the measurement model, [45]. Furthermore, due to low loadings, five (5) of the 28 items investigated (CF4, IA4, FinTech 5, ILS4, and ILS5) were excluded from the measurement model to improve model fitness. Table 2 shows the 23 item loadings that were kept because they exceeded the 0.7 threshold value, [46]. However in [47] one component, CRM4, was kept with a loading of 0.683.

Table 2. Reliability and Validity of Measurement Model

Construct	Items	Loadings	CR	AVE	VIF
Credit Flow	CF1	0.753	0.819	0.531	1.329
	CF2	0.726			1.314
	CF3	0.726			1.384
	CF5	0.710			1.346
Credit risk management	CRM1	0.721	0.813	0.521	1.292
	CRM2	0.739			1.511
	CRM3	0.760			1.539
	CRM4	0.683			1.185
	CT4	0.698			1.292
Financial Technology	FinTech1	0.722	0.865	0.617	1.470
	FinTech2	0.826			1.721
	FinTech3	0.821			1.757
	FinTech4	0.768			1.539
Information Asymmetry	IA1	0.938	0.884	0.719	2.727
	IA2	0.738			1.450
	IA3	0.857			2.286
Institutional Lending Structure	ILS1	0.796	0.835	0.560	1.487
	ILS2	0.707			1.569
	ILS3	0.755			1.605
	ILS6	0.727			1.289
Transaction Cost	TC1	0.877	0.913	0.724	2.315
	TC2	0.939			2.860
	TC3	0.793			2.020
	TC4	0.786			2.100

The AVEs for the constructs ranged from 0.521 (credit risk management) to 0.724 (transaction cost). Furthermore, the composite reliability for each construct was higher than the 0.700 threshold value that was advised. As a result, it is concluded that the measurement model was convergently valid. The ross-loadings, Fornell and Larker criterion, and Heterotrait-Monotrait (HTMT) criterion were utilized to examine discriminant validity. The factor loading for each item was at least 0.100 times the cross-loading value.

Furthermore, the square root of each construct's AVE had the highest correlation value, [48]. The HTMT for each build was less than the applied threshold value of HTMT 0.85, as indicated in Table 3, [49]. As a result, discriminant validity was established.

Table 3. The Heterotrait-Monotrait Ratio (HTMT) Criterion Results

Construct	CF	CRM	FinTech	IA	ILS	TC
CF						
CRM	0.274					
FinTech	0.566	0.086				
IA	0.259	0.264	0.174			
ILS	0.429	0.057	0.519	0.100		
TC	0.164	0.298	0.079	0.253	0.067	

4.2 Structural Model

First, without the moderating effects, the baseline model was evaluated. The internal variance inflation factor (VIF) values range from 1.185 to 2.860, which is less than the cutoff value of 5. (See Table 2). This shows no concerns with lateral collinearity in the study, [45]. Paper in [46] states that four criteria exist to evaluate the structure model. According to [50] the R-square would have a value of 0.75 for large, 0.50 for medium, and 0.25 for small. The results of this study show that TC, IA, CRM, ILS, and FinTech can explain 27.3% of the variance in CF. Predictive relevance (Q2) is the second requirement indicating whether the variables can predict the dependent variable. If the value of Q2 is greater than zero, the model is considered predictive, [48]. As shown in Table 5, the values of Q2 for CF in this study (Q2 = 0.13) are significantly higher than zero. In each of the study's paths, the value of f^2 was more than 0.02, [51] and [50], report that the impact magnitude is acceptable if f^2 is greater than 0,02. The path coefficient is the final criterion, which is evaluated in the following section.

4.1.1 Direct Effects

A 5000-sample complete bootstrapping with bias-Corrected and accelerated (BCa) at a significance threshold of 0.05 was used to get t-statistics for all path coefficients. A one-tailed test was chosen because each hypothesis is directed, [52]. Table 4 shows the effect size for each predictor construct on endogenous components.

Table 4. Structural Model Assessment (direct and effects results and decision)

H	f^2	Path	β-Path coefficient	Standard Deviation	t-Statistics	p-Value	Decision
H1	0.005	TC -> CF	-0.063	0.042	1.496	0.067	**Not accepted**
H2	0.012	IA -> CF	-0.097	0.043	2.262*	0.012	**Accepted**
H3	0.043	CRM -> CF	-0.184	0.047	3.938**	0.000	**Accepted**
H4	0.033	ILS -> CF	0.169	0.049	3.438**	0.000	**Accepted**
H5	0.145	FinTech -> CF	0.357	0.049	7.350**	0.000	**Accepted**

*Note: ** p< 0.01, *p < 0.05*

According to the analysis, except for H1, whose t-value was less than 1.645, all direct hypotheses (H2, H3, H4, H5) were accepted. The predictors of IA (β = -0.097, t = 2.262, p 0.012) and CRM (β = -0.184, t = 3.938, p=0.000) were related negatively to CF. ILS (β = 0.169, t = 3.438, p=0.000) and FinTech (β = 0.357, t = 7.350, p=0.00) were both positively associated with CF. TC, on the other hand, was not a significant predictor of CF (β = -0.063, t = 1.496, p = 0.067).

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Table 5. Construct cross-validated redundancy

Construct	Sum Square of Observations (SSO)	Sum Square of Errors (SSE)	Q2 = (1 - SSE/SSO)
CF	1,596.000	1,386.921	0.131
CRM	1,596.000	1,596.000	
FinTech	1,596.000	1,596.000	
IA	1,197.000	1,197.000	
ILS	1,596.000	1,596.000	
TC	1,596.000	1,596.000	

4.1.2 Moderating Analysis

The baseline model was extended to incorporate the moderator to evaluate a moderating effect in this study. This study employs a two-stage approach to moderation analysis. This strategy is advised if the study aims to see if the moderator significantly impacts the relationship, [53], [54]. Furthermore, the two-stage strategy has greater statistical power than the product-indicator or orthogonalizing approaches. Furthermore, the two-stage approach has more statistical power than the product-indicator or orthogonalization approaches, [55]. By reanalyzing, the measurement model's reliability and validity are confirmed. Table 6 depicts the structural model's evaluation with FinTech as the moderator. The interaction path's path coefficient (TC*FinTech) is 0.008 (t =0.154). According to [56] the minimum path coefficient value in the postulated path relationship between two variables should be approximately 0.10 to be statistically significant. As a result, this interaction path is not significant; hence, hypothesis H6 is not supported. Table 6 shows that hypotheses H7 and H8 are significant with a threshold of *t*- statistics *p* ≤0.1, as advocated by [46].

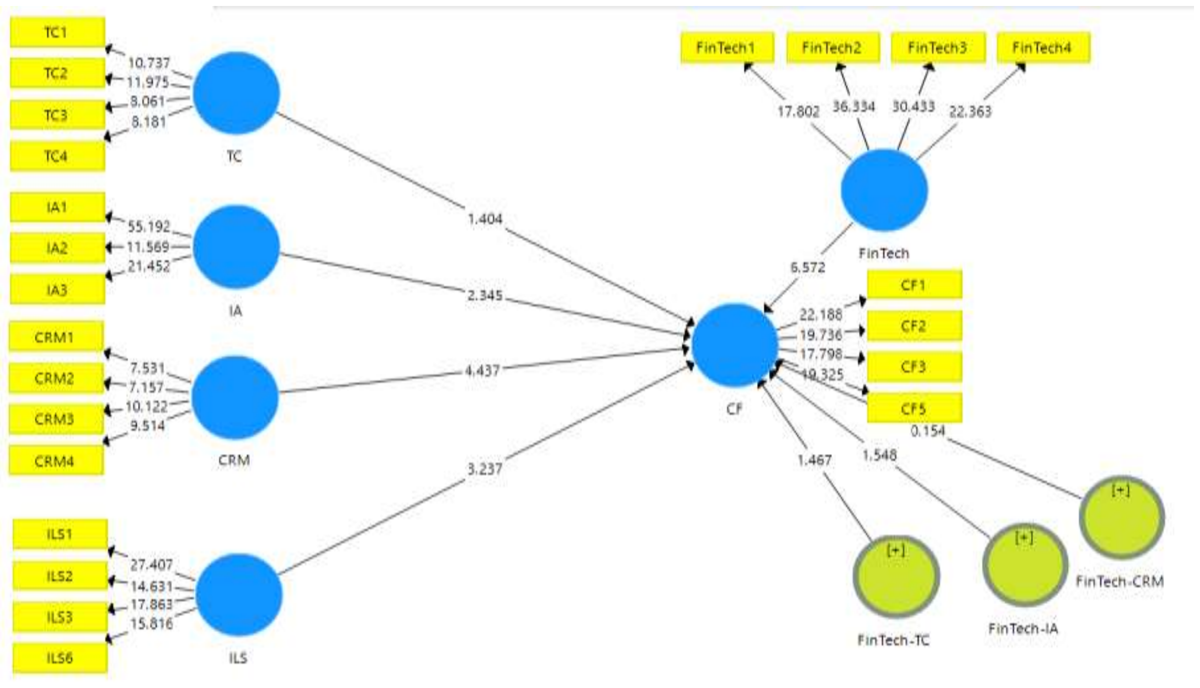

Fig. 2: The structural model

Table 6. Structural model assessment with the inclusion of FinTech as the moderator

Hypothesis	Path	Path Coefficient(β)	Standard Deviation (STDEV)	t Statistics (|β /STDEV|)	p-Value	Decision
H6	FinTech-TC -> CF	-0.008	0.050	0.154	0.439	**Not accepted**
H7	FinTech-IA -> CF	0.076	0.049	1.554*	0.060	**Accepted**
H8	FinTech-CRM -> CF	-0.084	0.058	1.455*	0.073	**Accepted**

*Note: *** p< 0.01, **p < 0.05, * p< 0.1 (based on one tailed test)*

Furthermore, in moderation analysis, the R^2 change becomes a critical concern. The baseline model has an R^2 of 0.273, whereas the interaction effect model has an R^2 of 0.282. The inclusion of the financial technology interaction factor changed R^2 by 3.2%, as seen by the R^2 change of 0.009 (additional variance). The following formula calculates the interaction effect magnitude, [45]

$$\boldsymbol{f^2} = \frac{R^2 \text{ with moderator included} - R^2 \text{ with moderator excluded}}{1 - R^2 \text{ with moderator included}}$$

$$\boldsymbol{f^2} = \frac{0.282 - 0.273}{1 - 0.282} = 0.05$$

With the f^2 of 0.05, FinTech has a medium influence size of moderation in this study, [57]. According to the author, more realistic thresholds for moderation's small, medium, and large impact sizes are 0.005, 0.01, and 0.025, respectively.
Alternatively, the three lines in Figure 3 depict the link between transaction costs (TC) and credit flow (CF). For higher levels of FinTech (for every standard deviation unit increase of FinTech), the negative relationship between TC and CF rises by the magnitude of the interaction term from -0.063 to -0.143 (-0.063 +(-0.008) = -0.143) because the green line slope is steep. On the other hand, for lower levels of FinTech (for every standard deviation unit fall in FinTech), the link between TC and CF reduces by the magnitude of the interaction term from -0.063 to -0.055 (-0.063 - (-0.008) = -0.055), because the slope of the red line is not steeper. In Table 6, the path coefficient of the interaction term between TC and CF is -0.008 less 0.10 to be statistically significant, as suggested by [56]. Additionally, the interaction term's t-statistics value of 0.154 at a p-value of 0.439 is statistically insignificant and below the advised threshold at a confidence interval of 0.1, [58]. This means that FinTech does not moderate the relationship between TC and CF.

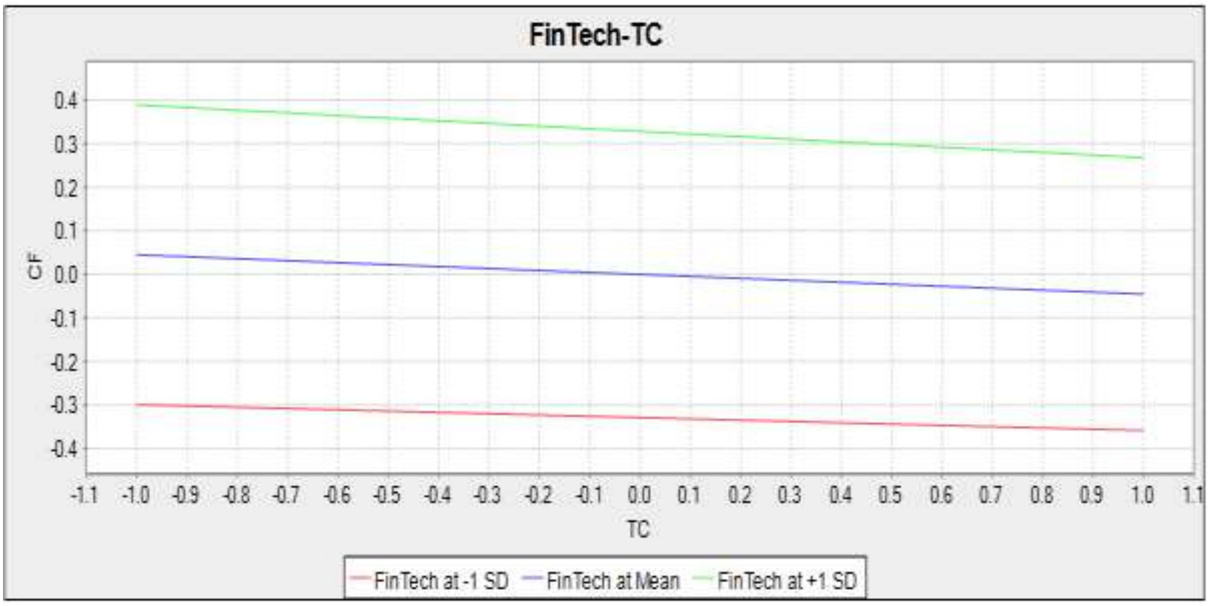

Fig. 3: Moderating effect of bank FinTech on the impact of transaction costs

Based on Figure 4, for higher levels of FinTech (for every standard deviation unit rise of FinTech – green line), the negative relationship between information asymmetry (IA) and bank credit flow

(CF) diminishes by the size of the interaction term from -0.097 to -0.021 (-0.097 +0.076) = -0.021) because the green line slope is not as steep. On the contrary, for lower levels of FinTech (for every standard deviation unit decrease of FinTech -red line), the negative relationship between IA and CF rises by the size of the interaction term from -0.097 to -0.173 (-0. 097 – 0.076) = -0.173), since the red line slope is steeper. In Table 6, the path coefficient of the interaction term between (IA) and (CF) is 0.076, approximately 0.10, to be statistically significant, as suggested by, [56]. Additionally, the interaction term's t-statistics value of 1.554 at a p-value of 0.060 and confidence interval of 0.1 is statistically significant, [58]. Conclusively, FinTech reduces the negative relationship between IA and CF.

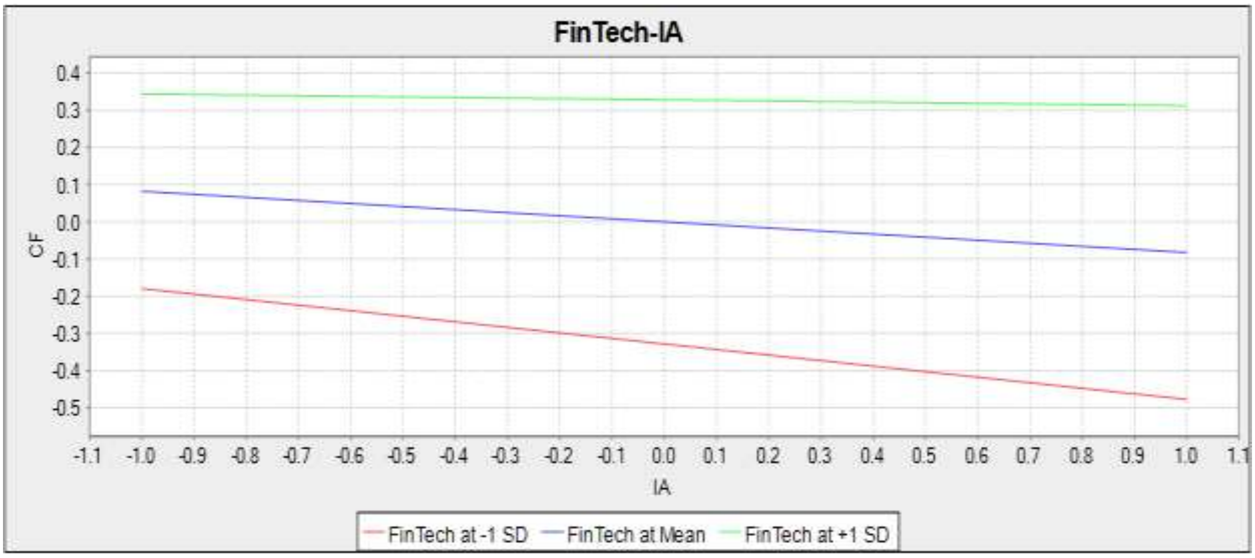

Fig. 4: Moderating effect of FinTech on the impact of information asymmetry

The three lines in Fig. 5 depict the link between credit risk management (CRM) and bank credit flow (CF) to AP-SMEs. For higher levels of FinTech (for every standard deviation unit increase of FinTech), the negative relationship between CRM and CF diminishes by the magnitude of the interaction term from -0.184 to -0.168 (-0.184 +(-0.084) = -0.168) because the green line slope is not steep. On the other hand, for lower levels of FinTech (for every standard deviation unit fall in FinTech), the link between CRM and CF rises by the magnitude of the interaction term from -0.184 to -0.21 (-0.184−(-0.084) = -0.21) because the slope of the red line is steeper. In Table 6, the path coefficient of the interaction term between CRM and CF is -0.082, approximately 0.10, to be statistically significant. Additionally, the interaction term's t-statistics value of 1.455 at a p-value of 0.073, with a confidence interval of 0.1, is statistically significant. This means that FinTech moderates the negative relationship between CRM and CF.

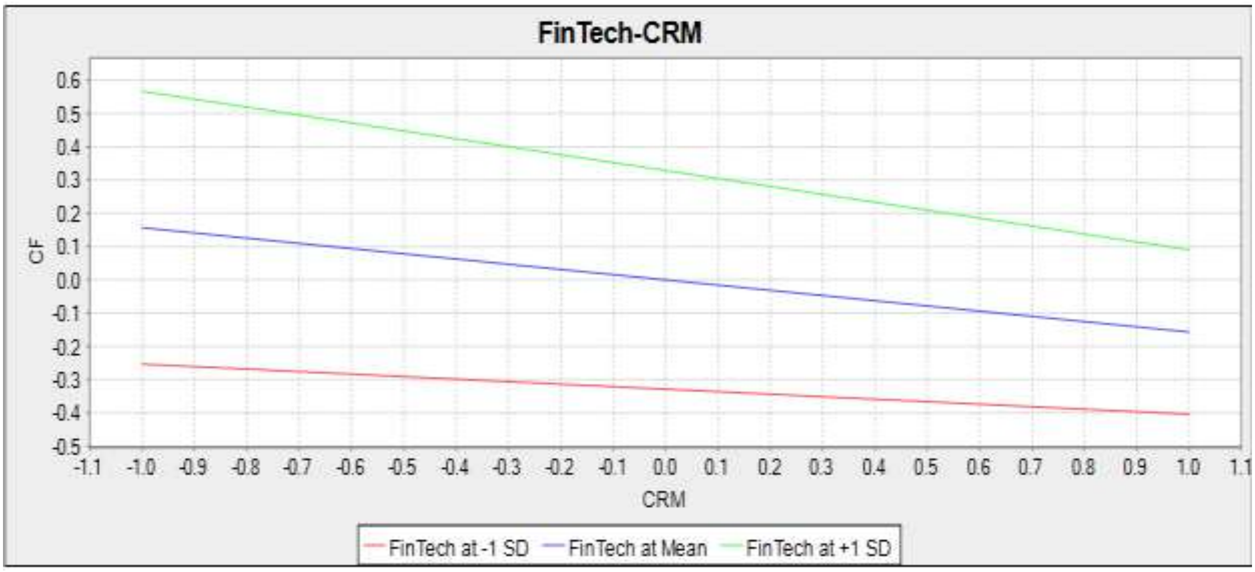

Fig. 5: Moderating effect of FinTech on the impact of credit risk management.

5 Discussion of Research Results

The impact of FinTech on banks' credit supply to Ap-SMEs is discussed in this paper, focusing on bank FinTech as a moderator. Our empirical research reveals that FinTech can promote the overall credit supply to Ap-SMEs from banks, based on a quantitative survey of loan officers from 399 bank branches in Tanzania. The study also considers transaction costs, information asymmetry, credit risk management, and institutional lending structures to reflect the theory of financial intermediation.

This study found that, contrary to earlier research, TC has no significant impact on CF to Ap-SMEs, [21], [19], [18]. The plausible reasons for the study's findings could be: First, commercial banks in Tanzania pass on the loan's lending expenses to the borrower. The cost is paid upfront by deducting from the extended amount. This means that even if the transaction costs of processing and servicing a loan are considerable, bankers will continue to issue credits because the expenses have been passed on to the borrowers, [59], [18]. Second, as [8] postulated, FinTech development in the credit market has lowered banks' transaction costs. Generally, TC in the Tanzanian commercial lending business would not impede offering loans to Ap-SMEs

According to this study, the banks' ILS show a high positive correlation with the flow of loans to Ap-SMEs. This finding is consistent with the findings of previous studies, which have emphasized the importance of not overlooking the positive effects of lending policies, rules, procedures, and other regulations on credit supply, [60], [28]. The findings show that commercial banks' tailored regulations, procedures, and lending policies increase credit flow to Ap-SMEs. On the other hand, commercial banks' lending policies and other structures could simplify the credit decisions of lending officers when extending loans to Ap-SMEs. Therefore, it is appreciated that the initiative to improve credit availability to any sector cannot be successful without considering institutional lending mechanisms.

In addition to the analysis, information asymmetry (IA) negatively impacts loan flow to Ap-SMEs. If commercial banks do not have adequate information to aid them in making credit decisions, they will be hesitant to lend to SMEs. This research backs up prior research that found a negative relationship between IA and CF, [61], [62]. It could be confirmed that banks' lending appetite for Ap-SMEs is limited because of their lack of information transparency, limiting the flow of loans. Consistent with our findings, this study also found that banks' credit risk management has a negative impact on credit flow to Ap-SMEs, [63], [64]. This supports the reality that commercial banks' techniques for lowering credit losses, such as covenants, stringent collateral requirements, credit rationing, loan securitization and high lending rates in Tanzania, almost result in SMEs' loan requests being denied. Banks are concerned about the long-term survival of ap-SMEs, and as a result, they have little faith in the industry and are hesitant to lend to them.

The findings also successfully justified the study's gap by demonstrating a significant direct relationship between FinTech and CF. Notably, the study showed FinTech to moderate the negative relationships of IA and CRM to CF. As a result, except for H6, two hypotheses (H7 and H8) were accepted. Furthermore, the direct hypothesis (H5) linking FinTech, and CF was confirmed. The outcomes of this study back up the idea that financial technology has a direct and significant impact on credit flow to agro-related SMEs. The findings are related to the financial intermediation theory, which says that developments in ICT have simplified the intermediation process to the point where the traditional reasons for banks' existence appear to have faded, [7]. Similarly, this research aligns with the previous literature, suggesting that FinTech is a powerful tool for SMEs' credit access, [30], [65], [9].

In terms of FinTech as a moderator, the outcomes of this study show that FinTech does not reduce the Tanzanian commercial banks' transaction costs. Tanzanian commercial banks have primarily stuck to traditional lending methods and other psychometric means of processing and assessing borrowers. Banks have not invested much in financial technology aspects like blockchain technology, machine learning and artificial intelligence. As a result, banks have failed to capitalize on advances in FinTech by digitizing lending transactions, which involve less documentation, fewer employees, and few physical branches. However, the current study supports the hypothesis that FinTech minimizes the negative link between IA and CRM and credit flow. FinTech has changed the supply of various banking services in bank operations, processing, and delivery outlets. According to previous studies, FinTech will likely assist banks in improving credit information availability and accuracy, expanding the number of information access channels and sources, [33], [10]. In other words, FinTech closes the information gap between banks and small businesses.

Furthermore, according to the same studies, sharing data with other banks' large databases could reduce the cost of identifying potential borrowers and credit risk. The findings of this study show that using bank FinTech increases banks' ability to innovate and creates a supportive environment for increasing loans to AP-SMEs. Fintech helps expand the availability of borrowers' information and lessens banks' risks when lending to the agro-processing sector.

6 Conclusion and Policy Implications

This research aimed to investigate the moderating effect of FinTech in Tanzania's commercial bank lending business and its impact on the supply side of credit delivery to Ap-SMEs. The study attempted to close the bank credit gap in Tanzania's agro-processing sector and offer ways to boost credit availability for the same sector and other SMEs. The financial intermediation theory relationships, alongside bank FinTech, were investigated to determine their impact on credit delivery to Ap-SMEs.

The findings have some critical theoretical implications from the supply side. FinTech execution has proven to be a helpful instrument for adjusting the unpredictability of bank credit availability in the agro-processing sector. The moderation role of FinTech has been assessed in this article, with a particular focus on the connection between FinTech and financial intermediation relationships. Several concerns were investigated, including bank transaction costs, information asymmetry in the credit market, credit risk management features, and bank lending structures. Overall findings show that FinTech significantly reduces the negative effects of IA and CRM on bank flow to Ap-SMEs. The results reflect that the higher the FinTech, the weaker the negative relationship between information asymmetry and bank credit risk management to the bank credit flow. Furthermore, the present study coincides with the available literature that institutional lending structures act as a catalyst for more loans to SMEs, [42], [26], [66].

The findings of this study add to the body of knowledge and offer policy implications for Tanzanian policymakers and commercial banks. First, FinTech companies and banks should develop software compatible with and readily accepted by Ap-SMEs for loan appraisals. Banks' easy acceptance and deployment of FinTech could boost lending to Ap-SMEs and lower the burden of lending expenses imposed on them. Commercial banks could connect loans to the agro-processing industry through technological advancements such as the internet of things, mobile services, cloud computing and big data analytics. Around the globe, it is well known that financial technology pulls out borrowers' information at 360 degrees around them, [14], [4], [9]. Commercial banks should strategize and utilize the potential of FinTech when processing and disbursing loans to Ap-SMEs. Generally, online applications and the automation of due diligence, loan servicing, and regulatory compliance may help the traditional lending process.

Secondly, The Tanzanian government must strengthen the information environment, the legal and judicial environment, and the tax and regulatory regime to achieve an industrial economy in this sector. Policymakers should reduce the effect of information asymmetry and credit risk management by digitalizing financial practices to expedite the loan application services, availability, and approval processes. We recommend that future research be duplicated further by integrating more credit dimensions and other lending financial institutions in the investigation to explore the impact of studied variables on loan supply in other countries. It will also be interesting to investigate the role of FinTech in microfinance institutions and other providers of funds to small businesses and compare their lending practices and business model to that of large commercial banks.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Justus Mwemezi carried out the conception and data gathering. Abdelhak Senadjki was responsible for the data analysis and Lau Lin Sea organized the study's methodology and literature review.