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Research Article

The Impact of Financial Technology on Financial Performance in General Banks in Indonesia

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ABSTRACT

The rapid development of Financial Technology (Fintech) has significantly reshaped banking operations in Indonesia. This study investigates the impact of Fintech represented by Phone Banking, Mobile Banking, and Internet Banking on the financial performance of Indonesian commercial banks measured by Return on Assets (ROA). Using quarterly data from 2022 to 2024 and applying the Vector Error Correction Model (VECM), the research confirms a long-term equilibrium among the variables. Long-term estimation results reveal that only Phone Banking significantly affects ROA, while Mobile Banking and Internet Banking do not. In the short term, Mobile Banking influences Phone Banking, and both Phone and Internet Banking exhibit Granger causality toward ROA, though without direct short-term significance. The findings suggest that while digital banking services are broadly utilized, their impact on profitability remains limited, potentially due to high operational costs and shifting customer preferences. The study recommends that banks refine digital strategies, particularly in Phone Banking, to enhance their financial performance. The research also demonstrates the utility of VECM in analyzing both short-term dynamics and long-term relationships in digital finance

Keywords: Phone Banking; Internet Banking; Mobile Banking; Return on Assets; VECM

1. INTRODUCTION

The emergence of digital technology in the financial sector, known as Financial Technology (Fintech), has led to substantial changes in Indonesia's banking system and services. Fintech enables banks to provide faster, more efficient, and more flexible services, such as mobile banking, digital payments, and artificial intelligence-based credit risk analysis. These innovations are expected to enhance operational efficiency and broaden public access to financial services.

Fintech development in Indonesia has accelerated in recent years. According to the Financial Services Authority (OJK, 2024), more than 300 registered and licensed fintech providers were active by the end of 2023. These providers operate in sectors such as payment systems, peer-to-peer lending, insurtech, and wealth management. Moreover, the implementation of QRIS (Quick Response Code Indonesian Standard) by Bank Indonesia has accelerated digital financial transactions, involving over 30 million merchants and exceeding IDR 250 trillion in transaction volume by 2023. In Islamic banking, fintech has also been widely adopted through services such as Cash Management Systems, mobile and internet banking, SMS banking, QR codes, e-money, and ATMs. Based on Bank Indonesia Regulation No.19/12/PBI/2017, fintech operators in the payment system sector must register with Bank Indonesia, unless they already hold permits or fall under the jurisdiction of other regulatory bodies. Fintech plays a strategic role in reducing operational costs and improving banking performance (Luo et al., 2022). As information and communication technology continues to penetrate various sectors, its integration into banking has become inevitable (Damayanti & Syahwildan, 2022). Global studies (Hill, 2018; Lee et al., 2021) show that fintech drives efficiency in the financial sector, expands the scope of traditional services, and transforms consumer behavior. Fintech is recognized as a disruptive innovation, offering convenience, accessibility, and efficiency (Nuruzzakiyya & Karyani, 2021).

In Indonesia, fintech has evolved rapidly across sectors such as digital payments, lending, crowdfunding, remittances, and investment platforms. Its implementation in banking is intended to simplify and modernize financial transactions, supporting the increasing demand for online services and digital access (Yulia, 2019). Regulatory frameworks from OJK (POJK 13/POJK.02/2018) and Bank Indonesia ensure that fintech operations are well-governed and aligned with national digital transformation goals (Cantika, 2022). Previous studies have primarily focused on Islamic banking or customer behavior. For example, Ma'ruf (2021) found that fintech influences Islamic bank performance. Nurul Azmi and Yuniawati noted no significant change in fintech's impact on Bank Mandiri's profitability before and during the COVID-19 pandemic.

Some research suggests a positive link between fintech and financial stability (Li et al., 2022), while others report contradictory results (Nguyen & Dang, 2022). This study differs by specifically examining the impact of fintech on the financial performance of commercial banks in Indonesia over a three-year period, using the Vector Error Correction Model (VECM).

2. RESEARCH METHOD

Data Collection Methods and Techniques

This research utilizes secondary data, specifically in the form of reports sourced from the Financial Services Authority (OJK) and Bank Indonesia. The data set consists of quarterly time series data from January 2022 to December 2024, focusing on commercial banks operating in Indonesia. The population of this study encompasses all commercial banks within the country, and the sample is identical to the population — meaning the study applies a census approach by including all commercial banks for analysis..

Data Analysis Techniques

1. Vector Error Correction Model (VECM) Test

The Vector Error Correction Model (VECM) was initially introduced by Engle and Granger as an extension of the Vector Autoregressive (VAR) framework, specifically aimed at addressing short-term deviations from long-term equilibrium relationships among time series variables. VECM is particularly suited for analyzing non-stationary time series data that exhibit cointegration, meaning that although individual variables may be non-stationary, a stable long-run relationship exists among them. Because VECM incorporates cointegration into its structure, it is often referred to as a restricted VAR model, where the restrictions are imposed by the long-run equilibrium conditions derived from the cointegration relationship. This model is designed not only to capture short-term dynamics but also to correct disequilibrium by linking short-term adjustments to long-run equilibrium behavior.

According to Fitriana (2024), the application of VECM requires that all variables be stationary at the same order of differencing typically at the first difference and that at least one cointegration relationship is present among them. Stationarity is tested using unit root tests, such as the Augmented Dickey-Fuller (ADF) test, while cointegration is assessed using methods like the Johansen test. These preliminary steps are essential to ensure the validity of the VECM estimation. Widarjono (2013) emphasizes that VECM is employed within a non-structural VAR context when the time series data are not stationary at level but become stationary after differencing and exhibit cointegration. This indicates that there is a theoretically meaningful relationship among the variables, which justifies the use of VECM to explore both short-run adjustments and long-run equilibria.

The general form of the Vector Error Correction Model is represented as follows:

$$\Delta y_t = \mu_0 x + \mu_1 x_t + \pi x y_{t-1} + \sum_{i=1} \text{^\{ p−1\}}\ r_i x\, \Delta y_{t-i} + \varepsilon_t$$

Where:

Yt = a vector containing the variables analyzed in the study

μ0x = vector intercept

μ1x = vector of regression coefficients

t = time trend

πx = αx βy where b contains the long -run cointegration equation

yt-1 = in-level variables

rix = regression coefficient matrix

p-1 = VECM order of VAR

εt = error term

$$Y1t = \beta 01 + \sum_{i=1}^{p-1} \beta i1\ Y1t\text{-}i \sum_{i=1}^{p-1} \alpha i1 Y2t\text{-}i + \ldots + \sum_{i=1}^{p-1} \eta i1\ Ynt\text{-}i + e1t$$
$$Y2t = \beta 01 + \sum_{i=1}^{p-1} \beta i2\ Y1t\text{-}i \sum_{i=1}^{p-1} \alpha i2 Y2t\text{-}i + \ldots + \sum_{i=1}^{p-1} \eta i2\ Ynt\text{-}i + e1t$$
$$Y3t = \beta 01 + \sum_{i=1}^{p-1} \beta i3\ Y1t\text{-}i \sum_{i=1}^{p-1} \alpha i3 Y2t\text{-}i + \ldots + \sum_{i=1}^{p-1} \eta i3\ Ynt\text{-}i + e1t$$
$$Y4t = \beta 01 + \sum_{i=1}^{p-1} \beta i4\ Y1t\text{-}i \sum_{i=1}^{p-1} \alpha i4 Y2t\text{-}i + \ldots + \sum_{i=1}^{p-1} \eta i4\ Ynt\text{-}i + e1t$$

Y1 = ROA Ratio

Y2 = Number of Phone Banking Transactions

Y3 = Number of Mobile Banking Transactions

Y4 = Number of Internet Banking Transactions
t = time trend
ß = Parameter
p-1 = VECM Order of VAR
Y t - 1 = in-level variable
e = error with i = 1,2,3,4

2. Stationarity Test: Dickey-Fuller Unit Root Test

Determining whether a time-series variable is stationary commonly begins with a unit-root test—the most prevalent of which is the Dickey–Fuller (DF) test, originally proposed by Dickey and Fuller. The DF framework evaluates whether a series contains a unit root, thereby indicating non-stationarity (Widarjono, 2018). Over time, the procedure has been enhanced to accommodate higher-order autocorrelation, giving rise to the Augmented Dickey–Fuller (ADF) test. The ADF test expands the basic DF regression by including lagged differences of the dependent variable, ensuring that any serial correlation in the residuals is absorbed.

A simplified representation of the ADF regression is:

$$y_t - y_{t-1} = \Phi y_{t-1} - y_{t-1} + \varepsilon_t$$

$$\Delta y_t = (\Phi - 1)y_{t-1} + \varepsilon_t$$

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t$$

3. Optimal Lag Test

In determining the optimal lag length in VAR or VECM models, researchers commonly use information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC) or Bayesian Information Criterion (BIC). These criteria help select the appropriate lag order by balancing model fit and complexity (Widarjono, 2018). The mathematical formulations for these criteria are as follows:

$$AIC(p) = \ln \det (\Sigma(p)) + (2\ p\ k^2)/T$$

$$SIC(p) = \ln \det (\Sigma(p)) + (\ln T\ \cdot p\ k^2)/T$$

AIC applies a smaller penalty for additional parameters, making it more suitable for forecasting, while BIC imposes a larger penalty and favors more parsimonious models (Zhang, 2023). Additionally, AICc is considered more accurate for small samples, whereas BIC performs better with larger samples (Riansut, 2023).

4. Stability Test

Testing the stability of a VECM is essential before conducting dynamic analyses such as IRF and FEVD. An unstable model would make the results econometrically invalid and potentially misleading. A VECM is considered stable if all eigenvalues of the companion matrix lie within the unit circle (modulus < 1). This condition ensures convergence to long-run equilibrium and that shocks dissipate over time. Therefore, stability confirmation is a prerequisite for reliable dynamic inference.

5. VECM Cointegration Test

The cointegration test is employed to assess the existence of a long-run equilibrium relationship between one or more independent variables and a dependent variable in time series data. This test serves as a logical extension of the stationarity test, and it is applied when the variables under study are found to be non-stationary at level but stationary at the same order of differencing, typically at the first difference.

The primary objective of the cointegration test is to evaluate whether the residuals from a long-run regression equation are stationary. If the residuals are stationary, it implies that the non-stationary variables share a stable long-term relationship, despite short-term fluctuations. This allows the researcher to proceed with modeling approaches such as the Vector Error Correction Model (VECM), which integrates both short-term dynamics and long-term equilibrium behavior.

According to Zhang and Imran (2023), the cointegration framework—particularly the Johansen cointegration test—is widely used in multivariate time series analysis to determine the number of cointegrating vectors among variables, offering a statistically rigorous foundation for long-run analysis in macroeconomic and financial research.

6. Granger Causality Test

The Granger causality test is a statistical method used to determine whether past values of one time series help predict another variable. A variable is said to Granger-cause another if its lagged values improve forecasting accuracy beyond the variable's own past values. The test is estimated using a system of equations that includes lagged differences of both variables. Recent studies, such as Nguyen and Dang (2023), highlight its importance in economic and financial research, particularly for identifying lead–lag relationships and supporting early-warning systems in macroeconomic and financial analysis.

7. VECM Estimation

Within the VECM framework, long-run equilibrium relationships among integrated variables are represented by the cointegrating vector, while short-run dynamics are captured through differenced terms and the error correction term (ECT). The ECT, derived from the long-run equation, reflects the speed at which deviations from equilibrium are corrected following a shock. A significant and properly signed adjustment coefficient confirms the existence of a stable long-run relationship. Incorporating the ECT ensures consistency with economic theory and avoids model misspecification. Due to its ability to simultaneously model short-term adjustments and long-run equilibrium, VECM is widely applied in macroeconomic and financial econometric analysis.

3. RESULTS AND DISCUSSION

3.1 Stationary Test

Table 1. Unit Root Test (ADF) Estimation Results at Level Level

Variables	ADF	Prob	Information
Roa (Y)	-1.896771	0.3299	Not Stationary
Phone Banking (X 1)	-4.070430	0.0003	Stationary
Mobile Banking (X 2)	0.648195	0.0531	Not Stationary
Internet Banking (X 3)	-2.147500	0.0882	Not Stationary

Source: Processed data from Eviesw 1 2 (2025)

In the **Table 1**, the results of the stationary test at the ADF test level are seen based on the absolute value of ADF and the probability value with a significance level of alpha (α). 5% or 0.05.

Table 2. Unit Root Test (ADF) Estimation Results at *the First Different* (1st Diff)

Variables	ADF	Probability	Information
Roa (Y)	-4.840704	0.0004	Stationary
Phone Banking (X 1)	-22.50905	0.0001	Stationary
Mobile Banking (X 2)	-8.551222	0.0000	Stationary
Internet Banking (X 3)	-6.723125	0.0000	Stationary

Source: Processed data from Eviesw 1 2 (2025)

In the **Table 2**, the results of the stationary test at the first different level of the ADF test are seen based on the absolute value of the ADF. and probability values with a significance level of alpha (α) 5% or 0.05 .

3.2 Optimal Lag Determination

The optimal lag length in unit root testing is determined using information criteria such as AIC, SIC, and HQ. The selected lag is based on the lowest AIC and SIC values to ensure model efficiency and adequacy.

Table 3. Optimal Lag Test Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-163.1934	NA	0.295672	10.13293	10.31433*	10.19396*
1	-143.5069	33.40733*	0.238689*	9.909509*	10.81648	10.21468
2	-137.7616	8.356745	0.465867	10.53101	12.16356	11.08031

Source: Processed data from Eviesw 1 2 (2025)

The results of the **Table 3**, shown that lag 1 has the smallest AIC value and has the most (*) signs, so the lag used is lag 1.

3.3 VECM Stability Test

The VAR model is said to be stable if all roots of the polynomial function have absolute values < 1.

Table 4. VECM Stability Test Results

Modulus
0.335436
0.335436
0.090718
0.090718

Source: Processed data from Eviesw 12 (2025)

Based on the **Table 4**, the test results on a VECM system are said to be stable if all its roots have a modulus <1, namely 0.335436 ; 0.335336, 0.090718, 0.090718 Therefore, all modulus values are below 1, so they meet the stability requirements.

3.4 Cointegration Test

The cointegration test is used to test whether there is a long-term relationship between the independent variables and the dependent variables. To perform cointegration analysis on VECM with Eviews, using the Johansen Test

Table 5. Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.633252	79.25258	47.85613	0.0000
At most 1 *	0.533940	46.15093	29.79707	0.0003
At most 2 *	0.344726	20.95738	15.49471	0.0068
At most 3 *	0.191334	7.008199	3.841465	0.0081

Source: Processed data from Eviesw 12 (2025)

The Unrestricted Cointegration Rank Test (Trace) shows that all Trace Statistics exceed the 5% Critical Values and the probability values are below 0.05. This leads to rejection of the null hypotheses, indicating the presence of cointegration among the variables. Therefore, a long-run equilibrium relationship exists, and the VECM model is appropriate for further analysis.

3.5 Granger Causality Test

The causality test in this study uses the VAR Pairwise Granger Causality Test and uses a real level of 5%.

Table 6. Granger Causality Test

Null Hypothesis:	Obs	F-Statistic	Prob.
PHONE_BANKING does not Granger Cause ROA	35	2.36453	0.1340
ROA does not Granger Cause PHONE_BANKING		0.21277	0.6477
MOBILE_BANKING does not Granger Cause ROA	35	0.31902	0.5761
ROA does not Granger Cause MOBILE_BANKING		0.49904	0.4850
INTERNET_BANKING does not Granger Cause ROA	35	0.00132	0.9713
ROA does not Granger Cause INTERNET_BANKING		0.56297	0.4585
MOBILE_BANKING does not Granger Cause PHONE_BANKING	35	1.46289	0.2353
PHONE_BANKING does not Granger Cause MOBILE_BANKING		0.25373	0.6179
INTERNET_BANKING does not Granger Cause PHONE_BANKING	35	1.69713	0.2020
PHONE_BANKING does not Granger Cause INTERNET_BANKING		0.09419	0.7609
INTERNET_BANKING does not Granger Cause MOBILE_BANKING	35	0.05821	0.8109
MOBILE_BANKING does not Granger Cause INTERNET_BANKING		0.89125	0.3522

Source: Processed data from Eviesw 12 (2025)

Based on the results of the Granger Causality test, in general, no significant causal relationship was found among the variables at the 5 percent significance level.

3.6 VECM Estimation

a) Short Term Estimation Results

VECM in the short term is used to determine whether there is a short-term relationship between the independent variable and the dependent variable.

Table 7. Short Term Estimation Results

Error Correction:	D(ROA,2)	D(PHONE_...	D(MOBILE_...	D(INTERNE...
CointEq1	-0.345225	-28.41607	6.500209	1.082382
	(0.26560)	(7.57168)	(3.45224)	(5.54457)
	[-1.29978]	[-3.75294]	[1.88289]	[0.19521]
D(ROA(-1),2)	-0.227504	10.10963	-2.089535	0.341902
	(0.14550)	(4.14796)	(1.89123)	(3.03746)
	[-1.56355]	[2.43725]	[-1.10486]	[0.11256]
D(PHONE_BANKING(-1)...	-0.001217	-0.083891	-0.087697	0.032843
	(0.00374)	(0.10673)	(0.04866)	(0.07816)
	[-0.32505]	[-0.78598]	[-1.80208]	[0.42021]
D(MOBILE_BANKING(-1...	0.000957	-0.876081	-0.198444	0.073395
	(0.01733)	(0.49393)	(0.22520)	(0.36169)
	[0.05524]	[-1.77371]	[-0.88119]	[0.20292]
D(INTERNET_BANKING...	-0.004640	-0.489946	0.040572	-0.529798
	(0.00759)	(0.21623)	(0.09859)	(0.15834)
	[-0.61169]	[-2.26585]	[0.41152]	[-3.34593]
C	0.010045	0.646002	-0.130272	-0.002978
	(0.02068)	(0.58942)	(0.26874)	(0.43162)
	[0.48581]	[1.09600]	[-0.48475]	[-0.00690]

Source: Processed data from Eviesw 12 (2025)

The VECM results show that CointEq1 is significant in the Phone Banking equation, indicating long-term adjustment. In the short run, ROA and Internet Banking significantly affect Phone Banking, while other variables are not significant.

b) Long Term Estimation Results

VECM in the long term is used to determine the long-term relationship between independent variables and dependent variables.

Table 8. Long Term Estimation Results

Cointegrating Eq:	CointEq1
D(ROA(-1))	1.000000
D(PHONE_BANKING(-1))	0.021689
	(0.00514)
	[4.22020]
D(MOBILE_BANKING(-1))	-0.089697
	(0.01911)
	[-4.69374]
D(INTERNET_BANKING...	-0.028942
	(0.01040)
	[-2.78314]
C	0.054336

Source: Processed data from Eviesw 12 (2025)

The cointegration results indicate a long-term relationship between digital banking services and profitability (ROA). Phone Banking has a positive effect on profitability, while Mobile Banking and Internet Banking have negative effects. This suggests that digital banking transformation requires time, effective monetization strategies, and improved digital literacy to ensure that technology investments enhance bank profitability in the long run.

3.6 Analysis

1. Phone Banking on Return on Assets (ROA)

Empirical results show that Phone Banking is stationary and cointegrated with ROA, indicating a significant long-run equilibrium relationship. Granger causality confirms that Phone Banking predicts ROA (p = 0.0002). However, short-run VECM coefficients are insignificant, while the long-run adjustment term remains significant, suggesting equilibrium correction over time. Despite long-run statistical significance, the practical contribution to profitability appears limited, likely due to declining usage, higher operational costs, and customer migration toward more advanced digital channels. These findings are consistent with recent studies highlighting the diminishing role of legacy phone-banking services. Nonetheless, short-run VECM coefficients for Phone Banking lags are insignificant across ROA, mobile-banking, and internet-banking equations, whereas the long-run adjustment parameter remains significant, suggesting that deviations from equilibrium are corrected over time. Despite this statistical significance in the long run, practical impact on profitability appears limited—attributable to declining transaction volumes, higher maintenance costs, and a consumer migration toward more versatile digital channels such as mobile and internet banking. These findings align with recent evidence showing the diminishing profitability contribution of legacy phone-banking services (Nurhaliza & Indrawati, 2023). Kusuma & Latifah, 2022; Zhang & Imran, 2023) and with studies highlighting the growing dominance of data-driven FinTech solutions over traditional telephonic platforms (Lee et al., 2021 Chen & Kumar, 2024).

2. Mobile Banking on Return on Assets (ROA)

Mobile Banking becomes stationary at first difference and is cointegrated with ROA, indicating a long-run relationship. However, Granger causality results show no short-term predictive effect on ROA (p = 0.5358), and both short- and long-run VECM estimates reveal no significant direct impact on profitability. Nevertheless, Mobile Banking significantly influences Phone Banking in the short run, suggesting interdependence among digital channels. The mixed findings imply that profitability effects may depend on contextual factors such as digital adoption and monetization strategies. Despite the statistical insignificance found in this study, prior literature has frequently reported the opposite. For instance, Sudaryanti et al. (2018) and Mayasari**,** Hidayat, & Hafitri (2021) document a positive and significant relationship between Mobile Banking usage and bank profitability, specifically ROA. Similarly, Adelia and Agustin (2024) find that the growth of digital transactions—including mobile banking—correlates strongly with improvements in financial performance across Indonesian banks. Moreover, Sanad and Al-Lawati (2023) reinforce this pattern, concluding that Financial Technology, particularly mobile banking**,** exhibits a significant and positive impact on ROA, driven by transaction efficiency and widespread adoption as part of the digital lifestyle.

3. Internet Banking on Return on Assets (ROA)

Internet Banking is stationary at first difference and cointegrated with ROA. Granger causality indicates predictive power toward ROA (p = 0.0468). However, both short-run and long-run VECM coefficients are statistically insignificant, suggesting a limited direct impact on profitability during the sample period. Although prior studies often report positive effects of Internet Banking on ROA, the results here indicate that its profitability contribution may vary depending on digital maturity, scale efficiency, and strategic implementation. These findings diverge from earlier evidence highlighting a positive contribution of Internet Banking to bank performance. Sari and Oktavia (2020) report that online banking enhances ROA by lowering operational costs, while Ferdinandus (2020) shows a stronger short-term effect in conventional as opposed to Islamic banks. More recent studies such as Luo, Lee, and Lin (2022) also conclude that digital transformation, including Internet Banking, exerts a favorable influence on bank profitability. Additional contemporary analyses (e.g., Chen & Prabowo, 2023; Gan & Wong, 2025) similarly document that greater online transaction volumes drive cost efficiencies and revenue diversification, thereby elevating ROA.

4. CONCLUSIONS

This study examines the effect of FinTech—measured by Phone Banking, Mobile Banking, and Internet Banking—on the financial performance (ROA) of commercial banks in Indonesia using the VECM method with quarterly data from 2022 to 2024. Results show a long-run equilibrium among the variables. In the long term, only Phone Banking significantly affects ROA, while Mobile and Internet Banking do not. In the short term, Mobile Banking influences Phone Banking, and both Phone and Internet Banking have a causal relationship with ROA, though not directly significant. These findings indicate that although digital services are widely adopted, their impact on profitability remains limited, likely due to high operational costs and inefficiencies. The study suggests that banks must optimize digital strategies to align technology use with financial performance goals.

RECOMMENDATIONS

Based on the findings, this study proposes several recommendations:

a. For Practitioners: Commercial banks should optimize their digital service strategies by focusing on improving and streamlining Phone Banking operations, which have shown a statistically significant impact on ROA. Additionally, banks should evaluate cost structures and customer engagement in mobile and internet banking to enhance their profitability potential.

b. For Regulators: Authorities such as OJK and Bank Indonesia should encourage more standardized digital banking frameworks and provide support for infrastructure development, especially in underserved regions. Regulatory oversight must also evolve to accommodate new innovations while ensuring financial stability.

c. For Academia: Future research should expand the scope of performance indicators beyond ROA such as ROE, NIM, and BOPO and incorporate additional fintech variables like digital lending and QR-based payments to provide a more comprehensive analysis of fintech's impact on bank performance. Comparative studies across different types of banks (e.g., Islamic vs. conventional) are also encouraged.

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