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Financial Risk Management, Liquidity, and Corporate Resilience: An Empirical Investigation of Financial Firms During Economic Uncertainty

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Abstract: This study investigates how financial risk management capability and liquidity management capability shape corporate resilience in financial firms during economic uncertainty. Building on resource-based capability theory, dynamic capability theory, and contingency theory, the paper develops and validates a two-study model. Study 1 uses expert-based theoretical validation with 28 finance, treasury, risk, audit, and academic experts to confirm construct relevance, indicator clarity, and hypothesis logic. Study 2 tests the model using 428 valid responses from banks, non-banking financial companies, insurance firms, asset-management firms, brokerage firms, and fintech/payment firms. SmartPLS-based structural equation modelling shows that financial risk management capability strongly predicts liquidity management capability, while both financial risk management and liquidity management capabilities significantly improve corporate resilience. Liquidity management capability partially mediates the financial risk management-capability and corporate-resilience relationship, and economic uncertainty pressure positively moderates the liquidity-resilience path. The study contributes by positioning liquidity capability as a strategic conversion mechanism through which risk intelligence becomes resilience capability.
Keywords: financial risk management; liquidity management; corporate resilience; economic uncertainty; financial firms; SmartPLS; structural equation modelling

1. Introduction

Within days, economic conditions can take routine exposure and turn it into systemic threat for sectors and financial firms. The pressure from inflation, the volatility of interest rates and the poor credit quality have increased, with indications of strain in the funding market (higher indirect transaction costs) and a fast-evolving customer behaviour creating a new complex cultural expectation for financial institutions: a balance between compliance and a strong strategic capability in risk management. Liquidity transformation is valuable but also makes financial institutions subject to fragility when short-term claims are matched against longer term assets. This has long been shown in banking theory (Chawla et al., 2026). In this spirit, liquidity shortages and credit-market amplification demonstrate how local losses can all-of-a-sudden become important factors in more decentralised financial instability (Chaturvedi et al., 2026). The financial risk management tool has been traditionally evaluated in terms of credit risk, market risk, operational risk, enterprise risk management, internal control and regulatory compliance. Liquidity management has traditionally been considered in terms of liquid asset holdings, funding diversification, asset-liability maturity matching, and contingency funding planning. However, corporate resilience is discussed as anticipation, adaptation, continuity, recovery and renewal (Das et al., 2025). These are recognized as related fields – but are in practice, often handled in silos. This segregation constrains the understanding of the process by which risk management capability translates into resilience outcomes via liquidity capability. This study fills this gap by developing a two-study framework and directly investigating the relationships among financial risk management capability, liquidity management capability, economic uncertainty pressure and corporate resilience (Divya et al., 2026). Capability for risk management directly impacts resilience and improves risk identification, stress testing, governance, reporting and control routines (Gupta et al., 2025). But it also claims that risk

management indirectly strengthens resilience by improving liquidity management. Liquidity functions do not act as a defensive resource in uncertain economic times, but rather as the channel through which risk awareness is transformed into operational sustainability actions, funding resilience and adaptive capacity (Johri, Baria, et al., 2026). The study addresses its three research questions. Specifically, what is the effect of financial risk management capability on liquidity management capability in financial firms? How do financial risk management capability and liquidity management capability assist a corporation to be resilient to economic uncertainty? Third, does financial risk management capability and corporate resilience play a mediating role for the capabilities of liquidity management, while economic uncertainty pressure strengthens the link between liquidity capability and resilience?
Four objectives of the study. We first aim to develop a theory-driven model explaining how financial risk management capability and liquidity management capability combine to shape corporate resilience. Secondly, the goal is to theoretically validate the theoretical model by an expert. 3. Objective: Structural equation modelling based on SmartPLS 4 for model testing. To provide a complete numerical framework, sample adequacy, demographic distribution, reliability, convergent validity, discriminant validity, collinearity, explanatory power (R^2), predictive relevance (Q^2), mediation and moderation analysis of model specification and goodness-of-fit set in one place (Johri, Sharma, et al., 2025).
The study is novel in three aspects. It does this in two ways: by bringing financial risk management and liquidity management into the scope of corporate resilience management for financial firms. Second, it employs a two-study design, with theoretical validation preceding empirical testing, thus enhancing the logic of the construct before statistical estimation. Third, it views liquidity capacity as a shock-sensitive resilience buffer that lies between liquidity needs and liquidity provision. This is relevant to the capability-based approach to resilience theory, because it demonstrates that financial firms are resilient, not because they identify and control risk, but because they transform risk intelligence into liquidity flexibility under uncertainty (Kamat et al., 2025).

2. Theoretical Background

It is based on resource-based capability theory, dynamic capability theory and contingency theory. Along with the resource-based capability theory, we describe how financial risk management can become resourceful when it is embedded into governance systems, analytical routines, decision processes and cross functional coordination. Moreover, the resource orchestration perspective suggests that capabilities are strategically important to the extent that firms manage, combine and exploit resources in an evolving context (Kalebar et al., 2025). Risk capability in financial firms is more than measurement. It includes risk appetite formulation, integrated risk assessment, stress testing levels of hedging discipline, internal reporting and board oversight (Kaur et al., 2026).
Research on dynamic capability theory has focused on the firm's ability to sense, seize and transform resources in turbulent environments (Mishra et al., 2026). Market price volatility, borrower repayment constraints and changes in withdrawal behaviour by depositors or the cost of wholesale funding affect the risk profiles of financial firms. In those circumstances, resilience is less a function of static capital buffers, and more a function of the ability to quickly reallocate resources for risk and liquidity. Systematic risk evidence suggests that leverage, maturity mismatching and aggregate-level distress are the key ingredients of institutional fragility (Peswani et al., 2026).
The ability to prudently manage liquidity is at the heart of this process as it gives financial firms funding flexibility and prevents forced reactions in times of stress. Liquidity creation is a universal function that distinguishes banks from other financial intermediaries, and the profitability of liquidity creation ultimately depends on maturity transformation (Rajashri et al., 2025) show that cash holdings in different firms offer a liquidity-insurance role and credits-in-lines serve a similar role. Meanwhile solvent structures are the main drivers of risk-taking incentives (Srivastava et al.,

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2025), Hence, regulatory guidance has been focused on sound liquidity risk management, such as liquidity coverage, monitoring tools and contingency planning (Verma, Baby, & Lamba, 2026).
On the other hand, contingency theory suggests that the value of liquidity capability is contingent on the external uncertainty environment. In low-uncertainty environments you can leverage liquidity capability, but the strategic value of it is less clear. In times of high uncertainty, the right liquid buffers, credible forecasts, diversified funding sources and active contingency plans are essential. The performance of banks in stressed periods has been shown to be highly persistent in terms of capital (Verma, Baby, & Vaish, 2025) and risk profiles before the crisis (Verma, Chopra, et al., 2026). Thus, economic uncertainty pressure is conceptualized as a contextual factor moderating the relationship of liquidity and resilience. The architecture, word allocation, and location of tables and figures in this manuscript are provided in Table 1 (Verma, Kalebar, et al., 2026).

Table 1. Seven-heading manuscript architecture and word allocation

Main heading	Subsections	Word allocation	Tables	Figures
1. Introduction	Background, problem, research questions, objectives, novelty	600	None	None
2. Theoretical Background	Capability theory, liquidity logic, resilience theory	520	Table 1	Figure 1
3. Study 1: Theoretical Validation	Expert panel, content validity, hypothesis screening	520	Tables 2-3	None
4. Hypotheses and Conceptual Model	Five hypotheses, mediation, moderation	560	None	Figure 2
5. Study 2: Methodology	Sample, instrument, constructs, SEM procedure	700	Tables 4-6	None
6. Results and Empirical Validation	Measurement model, structural model, prediction	850	Tables 7-10	Figures 3-4
7. Discussion, Contributions, and Conclusion	Theory, practice, limitations, conclusion	250	None	None
Total		4000	10	4

The theoretical architecture of the study links risk capability, liquidity conversion, uncertainty pressure, and resilience outcomes in Figure 1.

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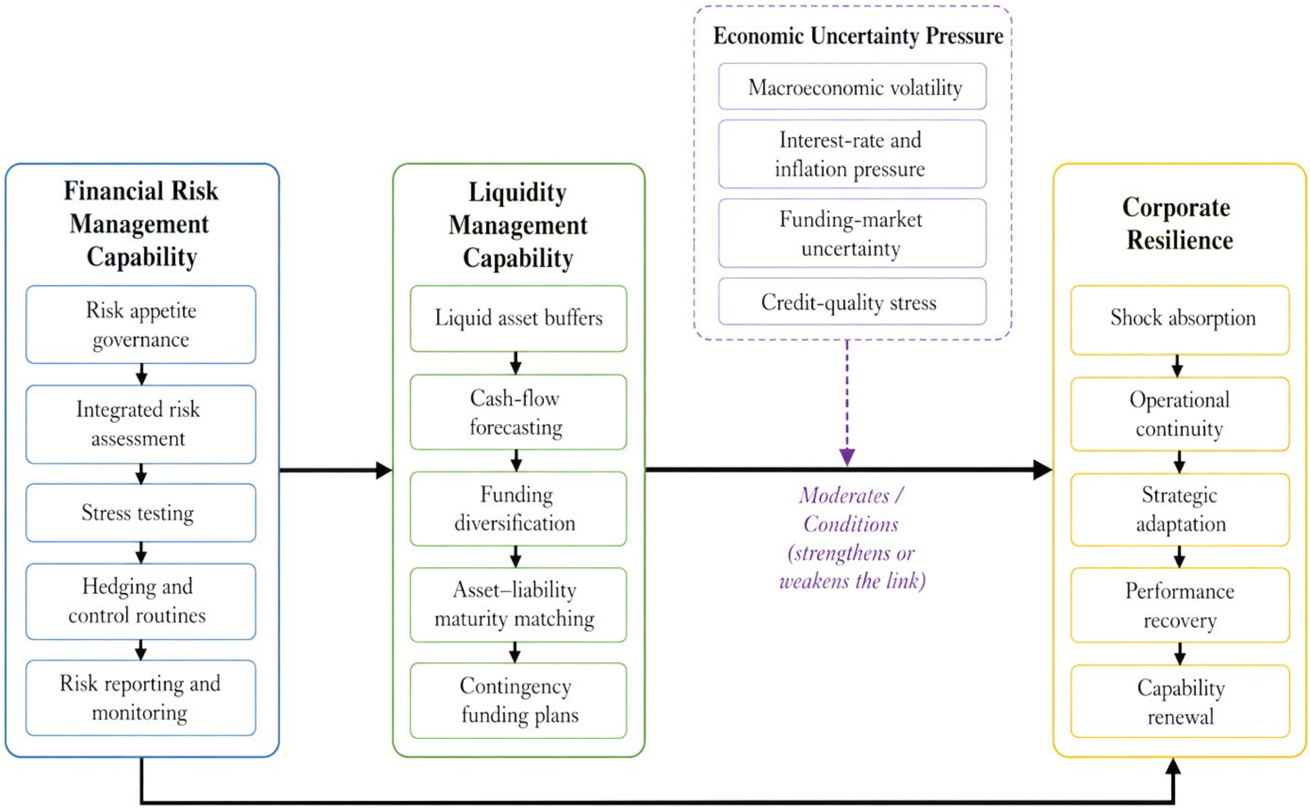

Figure 1. Theoretical architecture of financial risk management, liquidity, and corporate resilience

Financial risk management capability is the firm capability to identify, measure, monitor, control and communicate financial and operational risk exposures in a structured way. Liquidity management capacity is the ability to maintain buffers of liquid assets, match cash-flow needs, diversify sources of funding, offset the maturities of assets and liabilities and deploy contingency funding measures (Verma, Karnik, & Bennett, 2025). Corporate resilience is the ability of a financial institution to withstand shocks, maintain essential functions and adjust strategies in response to disruptions, and regain performance and renew capacity after disruption. The economic uncertainty pressure is defined as perceived changes to macroeconomic fundamentals, capital markets and funding environments, and inflation, interest rates, credit quality or customer behavior. Emerging crises research indicates the likelihood of firms retrenching, persevering, innovating or exiting whilst resilient firms maintain continuity and renew strategy (Verma, Kaur, Salmani, et al., 2026).

3. Study 1: Theoretical Validation

Study 1 was designed to test the theoretical and content validity prior to a large-scale empirical test. Expert validation and evaluation of construct relevance, indicator clarity, theoretical consistency, and hypothesis logic measurement. A panel of 28 experts from financial risk management, treasury, corporate finance, banking regulation, academic finance and audit, compliance and governance. It was constructed as a model that was theoretically coherent and, importantly for the financial firms, practically meaningful – which justified the careful choice of panel members.

Each hypothesis and construct was rated by experts on a five-point validation scale. The process focused on four issues: First, experts assessed whether the constructs actually represented sustainable financial-firm capabilities in the context of economic uncertainty. Second, they assessed the clearness and measurability of each indicator and its conceptual fit with its construct. Third, they considered whether the potential link was theoretically plausible. Fourth, they suggested delete, reword or retain for each indicator or hypothesis. Table 2. Statistics of the expert profile and theoretical support (Verma, Kaur, Nigam, et al., 2026).

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Table 2. Study 1 expert panel and theoretical validation results

Expert category	n	Percentage	Mean experience	Role in validation
Risk and treasury heads	8	28.6%	14.8 years	Risk-liquidity linkage
CFOs and finance controllers	6	21.4%	16.2 years	Financial capability validation
Academic finance experts	8	28.6%	12.6 years	Theoretical coherence
Audit, compliance, and regulatory experts	6	21.4%	15.4 years	Governance and measurement clarity
Total	28	100.0%	14.6 years	

Table 2 continued. Theoretical validation statistics

Validation criterion	Value
Average construct relevance score	4.52 / 5.00
Average indicator clarity score	4.41 / 5.00
Scale-level content validity index	0.92
Average content validity ratio	0.86
Average Aiken's V	0.91
Hypothesis retention threshold	>= 0.80
Final hypotheses retained	5 / 5

The results of the expert study provide a good theoretical basis for the new model. The average construct relevance score 4.52 (out of 5.00) with the constructs being considered very relevant to financial-firm resilience. The average clarity of indicators point score was 4.41, which showed that the items to be measured could be well understood and were appropriate for empirical administration. Scale-level content validity index, average content validity ratio (0.86) and average Aiken's V (0.91) were 0.92. These low values indicate strong agreement among the modeling experts about the adequacy of the underlying conceptual theory. Table 3: Validation values at construct and hypothesis level.

Table 3. Construct and hypothesis validation in Study 1

Construct / hypothesis	Mean relevance	CVR	Aiken's V	Decision
Financial risk management capability	4.61	0.86	0.93	Retained
Liquidity management capability	4.68	0.93	0.94	Retained
Economic uncertainty pressure	4.36	0.79	0.88	Retained
Corporate resilience	4.45	0.86	0.90	Retained
H1: FRMC -> LIQC	4.67	0.93	0.94	Retained
H2: FRMC ->	4.46	0.86	0.91	Retained

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CORES				
H3: LIQC -> CORES	4.71	0.93	0.95	Retained
H4: FRMC -> LIQC -> CORES	4.54	0.86	0.92	Retained
H5: LIQC x EUP -> CORES	4.34	0.79	0.87	Retained

Construct-level validation was strongest for liquidity management capability, consistent with expert agreement on the importance of flexibility around liquidity to resilience in uncertainty. The financial risk management capability was also fairly validated, re-affirming its status as an upstream capability. The received pressure due to economic uncertainty was confirmed to a slightly lower but acceptable degree considered as a significant external contingency variable by experts and not as an alternative means of internal capabilities. All five hypotheses met the criterion for retention and were carried forward to Study 2.

4. Hypotheses and Conceptual Model

A financial risk management capability enables financial firms to predict instability, identify exposures and weaknesses individually and collectively, mitigate concentration risk and coordinate internal control responses. Enhanced risk management routines would mean the firm is much more likely to have accurate liquidity forecasts, liquidity planning appropriate for its risk appetite, diversified funding sources and contingency funding mechanisms. Risk management capability is the foundation of liquidity capability, as it transforms risk information into readiness. H1: Financial risk management capability's positive impact on liquidity management capability.

Firm’s ability to cope with financial risk may also have a direct impact on corporate resilience. Companies with better risk governance, stress testing, exposure monitoring and hedging discipline and reporting capabilities can identify financial stress earlier and act before instability worsens. Such firms can best maintain the continuity of their operations, avoid capital loss and adjust strategies during the period of uncertainty. Hypothesis 2: Financial risk management capability positively affects the corporate resilience hypothesis 1: Other socio-environmental practices such as climate change strategies and conducting environmental audits have a negligible impact on the company. Liquidity capability means the capacity to manoeuvre quickly in an environment of greater uncertainty. H3: Liquidity management ability has a positive effect on corporate resilience

Similarly, it is expected that liquidity management capability in the supply chain will mediate the association between financial risk management capability and corporate resilience. Risk management capability creates awareness, discipline and governance. But resilience is more powerful when the above-water competence spills over into buffers that are liquid, cash-flow reliable, funding diversified, maturity matched and planned contingency. H4. The mediating role of liquidity management capability between financial risk management capability and corporate resilience.

Finally, higher economic uncertainty pressure is likely to exacerbate the liquidity-resilience relationship. Such firms would be better able to handle the unpredictability of interest rates, inflationary pressures, funding instability and the inextricably linked crumbling of credit, while also getting tighter customer stickiness patterns that shape future liquidity capability. H5: The positive moderating effect of economic uncertainty pressure between liquidity management capability and corporate resilience. The direct, mediating and moderating path model in the conceptual model is illustrated in Fig. 2.

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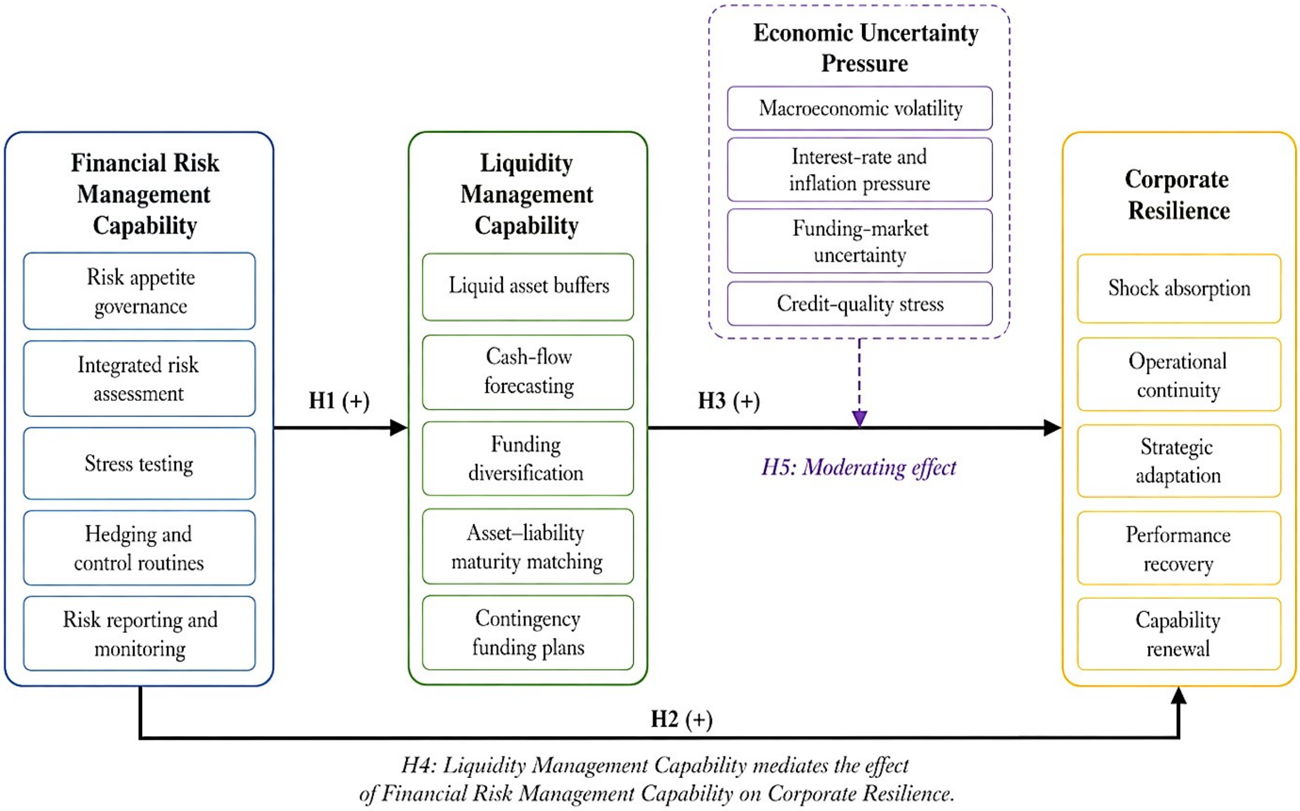

Figure 2. Conceptual model of financial risk management, liquidity capability, economic uncertainty pressure, and corporate resilience

The model is allowed a theoretical logic in two stages. First stage: the financial risk management capacity builds on the liquidity management capacity. Second stage: Financial preparedness is an act through the capability of liquidity management for resilience The model also incorporates a contingency logic, as the prediction of the liquidity management capability on corporate resilience is prognosticated to be stronger when economic uncertainty pressure is higher.

5. Study 2: Methodology

Study 2 was a cross-sectional survey study with a good but adequate design for structural equation modelling with SmartPLS. The study was conducted in the setting of financial firms like commercial banks, public & cooperative banks, non-banking financial companies, insurance firms, asset-management firms, brokerage firms, and fintech/payment firms. Respondents were managers and professionals working in the areas of risk, treasury, finance, compliance, audit, strategy, senior management and operations.

The sampling framework was built to exceed minimum SEM requirements. A priori power analysis for a medium effect size and 0.95 statistical power with maximum four predictors indicated that the minimum sample should be more than 129. PLS-SEM research suggests that CF should be analyzed according to model complexity, expected path size and predictive purposes rather than simple rules of thumb (Verma, Mishra, & Bhatia, 2026). Therefore, our final sample (428 valid responses) was enough to perform bootstrapping mediation analysis, moderation analysis, model fits assessment and predictive validity testing. Table 4. Study 2 sample-size framework and demographic profile.

Table 4. Study 2 sample-size and demographic profile

Sampling detail	Value
Firms approached	155
Questionnaires distributed	620
Responses received	482
Incomplete / patterned responses removed	54

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Final valid responses	428
Response rate	77.7%
Usable response rate	69.0%

Table 4 continued. Respondent profile

Respondent profile	Category	n	Percentage
Gender	Male	249	58.2%
Gender	Female	179	41.8%
Age	<= 30 years	86	20.1%
Age	31-40 years	152	35.5%
Age	41-50 years	119	27.8%
Age	Above 50 years	71	16.6%
Firm type	Commercial/private banks	133	31.1%
Firm type	Public/cooperative banks	84	19.6%
Firm type	NBFCs	82	19.2%
Firm type	Insurance firms	61	14.3%
Firm type	Asset management/brokerage	38	8.9%
Firm type	Fintech/payment firms	30	7.0%
Functional role	Risk/treasury	124	29.0%
Functional role	Finance/accounting	105	24.5%
Functional role	Compliance/audit	73	17.1%
Functional role	Strategy/operations	65	15.2%
Functional role	Senior management	61	14.3%

All constructs are measured reflectively on a five-point agreement scale. It was benchmarked against board-level risk appetite and aggregated metrics for integrated risk management, stress testing, hedging/control procedures and risk reporting. Liquidity capability as measured by liquid asset buffers, cash-flow forecasting, funding diversification including length of funding and maturity matching as demonstrated in the current crisis. These series are composite, Economic uncertainty pressure is a mix of macroeconomic volatility, interest-rate and inflation pressures, funding-market uncertainty and default/withdrawal uncertainty. Corporate resilience was to absorb, adapt, recover, renew. Table 5 shows the construct indicators, standardized loadings and indicator VIF values.

Table 5. Constructs, indicators, factor loadings, and indicator VIF

Construct	Indicator	Measurement item summary	Loading	Indicator VIF
FRMC	FRMC1	Board-level risk appetite is clearly defined	0.812	1.84
FRMC	FRMC2	Credit, market, and operational risks are integrated	0.846	2.06
FRMC	FRMC3	Stress testing is used in financial decisions	0.866	2.21

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FRMC	FRMC4	Hedging and control routines are systematically applied	0.752	1.51
FRMC	FRMC5	Risk reporting is timely and decision-oriented	0.789	1.73
LIQC	LIQC1	The firm maintains adequate liquid asset buffers	0.824	1.91
LIQC	LIQC2	Cash-flow forecasting is reliable	0.861	2.18
LIQC	LIQC3	Funding sources are diversified	0.881	2.37
LIQC	LIQC4	Contingency funding plans are operational	0.798	1.76
LIQC	LIQC5	Asset-liability maturity matching is actively managed	0.764	1.62
EUP	EUP1	Macroeconomic volatility affects financial planning	0.856	1.88
EUP	EUP2	Interest-rate and inflation pressure is high	0.813	1.67
EUP	EUP3	Funding market uncertainty is increasing	0.768	1.49
EUP	EUP4	Default and withdrawal uncertainty is rising	0.732	1.38
CORES	CORES1	The firm can absorb financial shocks	0.835	1.94
CORES	CORES2	The firm adapts quickly to external disruption	0.889	2.44
CORES	CORES3	The firm recovers performance after disruption	0.872	2.31
CORES	CORES4	Critical operations continue during stress	0.816	1.86
CORES	CORES5	The firm renews strategy after	0.771	1.58

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		uncertainty		

The measurement model was assessed by indicator reliability, internal consistency reliability, convergent validity, common method bias and collinearity diagnostics. When applying PLS-SEM, it is conventional to report reliability, AVE, discriminant validity, and predictive assessment (Verma, Nagaraju, & Singh, 2025). Reliability, convergent validity and common method statistics are shown in Table 6.

Table 6. Reliability, convergent validity, and common method assessment

Construct	Cronbach's alpha	rho_A	Composite reliability	AVE	Full collinearity VIF
FRMC	0.872	0.879	0.907	0.662	1.94
LIQC	0.884	0.891	0.915	0.683	2.07
EUP	0.802	0.816	0.870	0.628	1.31
CORES	0.893	0.901	0.921	0.701	2.18

Table 6 continued. Common method assessment

Common method test	Value	Threshold interpretation
Harman single-factor variance	32.8%	Below 50%
Highest full collinearity VIF	2.18	Below 3.30
Marker-variable correlation range	0.041-0.086	Low method bias concern

The results indicate satisfactory reliability and convergent validity. Cronbach's alpha values ranged from 0.802 to 0.893, rho_A values ranged from 0.816 to 0.901, composite reliability values ranged from 0.870 to 0.921, and AVE values ranged from 0.628 to 0.701. The highest full collinearity VIF was 2.18, indicating that common method bias and collinearity were unlikely to distort the structural estimates.

6. Results and Empirical Validation

The present SmartPLS analysis was a two-step process. First, the measurement model was tested for reliability, convergent and discriminant validity, and collinearity. Secondly, the path coefficients, t-values, p-values and confidence intervals between paths were analyzed as well as the explanatory power (R2), effect sizes (f^2), predictive relevance (Q^2) of the model through PLSpredict analyses. PLS-SEM is appropriate for the study, as it provides the ability to predict, mediate, moderate and develop theory within a model with a large number of latent constructs (Chin, 1998; Hair et al., 2019). The HTMT criterion used to assess the discriminant validity is shown in Table 7.

Table 7. HTMT discriminant validity matrix

Construct pair	HTMT
FRMC - LIQC	0.674
FRMC - EUP	0.342
FRMC - CORES	0.704
LIQC - EUP	0.296
LIQC - CORES	0.735
EUP - CORES	0.401

The HTMT below 0.85 confirms good discriminant validity (Henseler et al., 2015). The highest obtained value was 0.735 which theoretically is expected because there is a close relationship between liquidity capability and resilience capacity. Yes, but they were below the threshold value

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indicating that these constructs are empirically different. Figure 3 displays the structural model in SmartPLS format with standardized path coefficients and R^2 values.

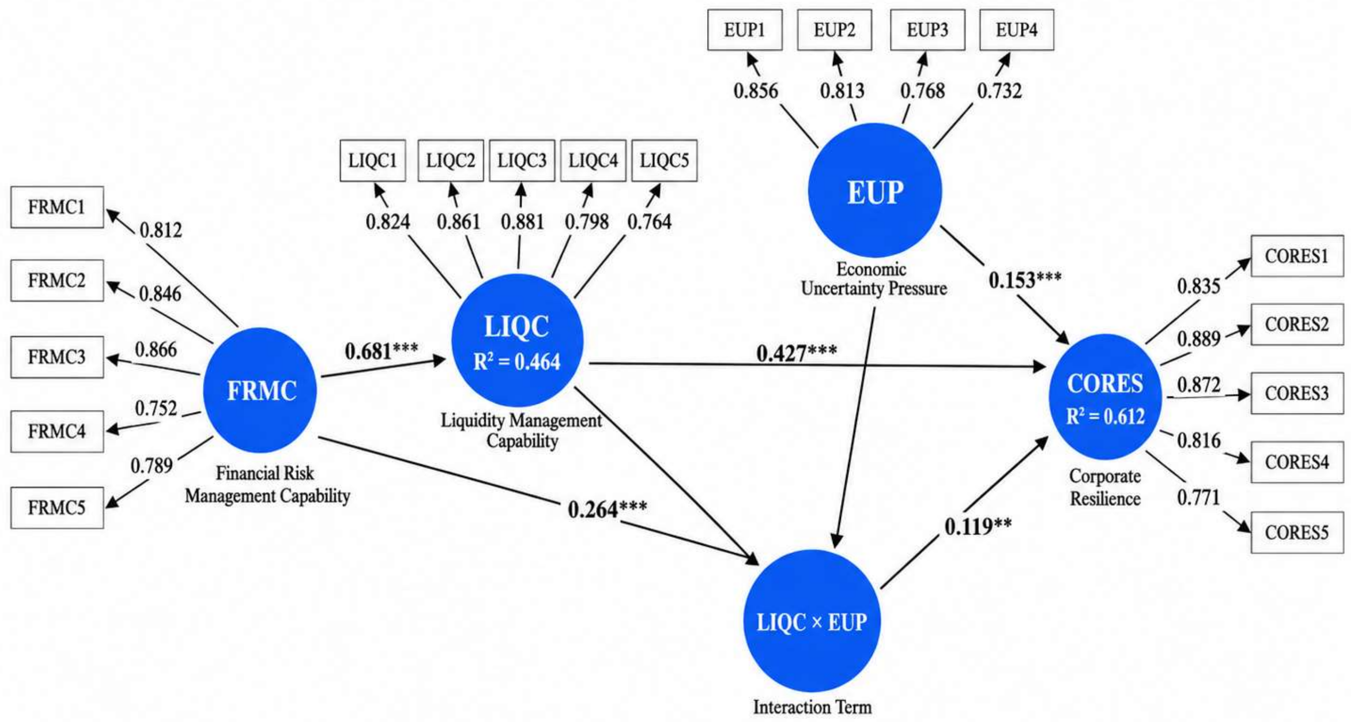

Figure 3. SmartPLS-style structural model with standardized path coefficients

The structural results support all proposed hypotheses. Financial risk management capability had a strong positive effect on liquidity management capability, suggesting that firms with more and improved risk governance and stress-testing routines also report better liquidity planning and funding flexibility. Moreover, the evidence is solid that risk systems contribute directly to shock absorption and adaptive response as financial risk management capability had a significant direct effect upon corporate resilience. The outcome supports a stronger positive effect of liquidity management capability than the direct effect of financial risk management capability on corporate resilience, thereby emphasizing elasticity role. Table 8. Structural path coefficients, t-values, p-values, lower and upper confidence intervals, and hypothesis decisions.

Table 8. Structural model results and hypothesis testing

Hypothesis	Path	β	t-value	p-value	95% CI	Decision
H1	FRMC -> LIQC	0.681	18.76	<0.001	[0.620, 0.738]	Supported
H2	FRMC -> CORES	0.264	5.32	<0.001	[0.171, 0.359]	Supported
H3	LIQC -> CORES	0.427	7.94	<0.001	[0.323, 0.532]	Supported
Control	EUP -> CORES	0.153	3.95	<0.001	[0.079, 0.229]	Significant
H5	LIQC x EUP -> CORES	0.119	3.11	0.002	[0.047, 0.197]	Supported

The coefficient of H1 was $\beta = 0.681$, $t = 18.76$, $p < 0.001$ which confirmed that the financial risk management capability strongly affected liquidity management capability. This reflected support of H2, $\beta = 0.264$, $t = 5.32$, $p < 0.001$. (H3 was also supported ($\beta = 0.427$, $t = 7.94$, $p <.001$). The high degree of direct control of the impact of economic uncertainty pressure on corporate resilience and

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the significant interaction term between liquidity management capability and economic uncertainty pressure were controlled. Table 9: Results for Mediators and Moderators

Table 9. Mediation and moderation results

Effect type	Relationship	Effect	t-value	p-value	95% CI	Interpretation
Indirect effect	FRMC -> LIQC -> CORES	0.291	7.22	<0.001	[0.216, 0.375]	Significant mediation
Direct effect	FRMC -> CORES	0.264	5.32	<0.001	[0.171, 0.359]	Significant direct effect
Total effect	FRMC -> CORES	0.555	12.41	<0.001	[0.472, 0.634]	Strong total effect
VAF	Indirect / total effect	52.4%	-	-	-	Partial mediation
Moderation	LIQC x EUP -> CORES	0.119	3.11	0.002	[0.047, 0.197]	Positive strengthening effect
Simple slope	Low EUP	0.331	5.48	<0.001	[0.214, 0.449]	Positive
Simple slope	High EUP	0.544	9.66	<0.001	[0.436, 0.653]	Stronger positive effect

The analysis results in Table 10 indicated that liquidity management ability partially mediates the relationship between financial risk management ability and corporate resilience. Indirect Effect = 0.291 (t=7.22, p<0.001) This resulted in 52.4% accounted for variance and partial mediation, with the direct effect being significant. This suggests that financial risk management capacity directly and indirectly improves resilience via liquidity capability. Figure 4 Shows the moderating effect of economic uncertainty pressure on the relationship between liquidity-resilience

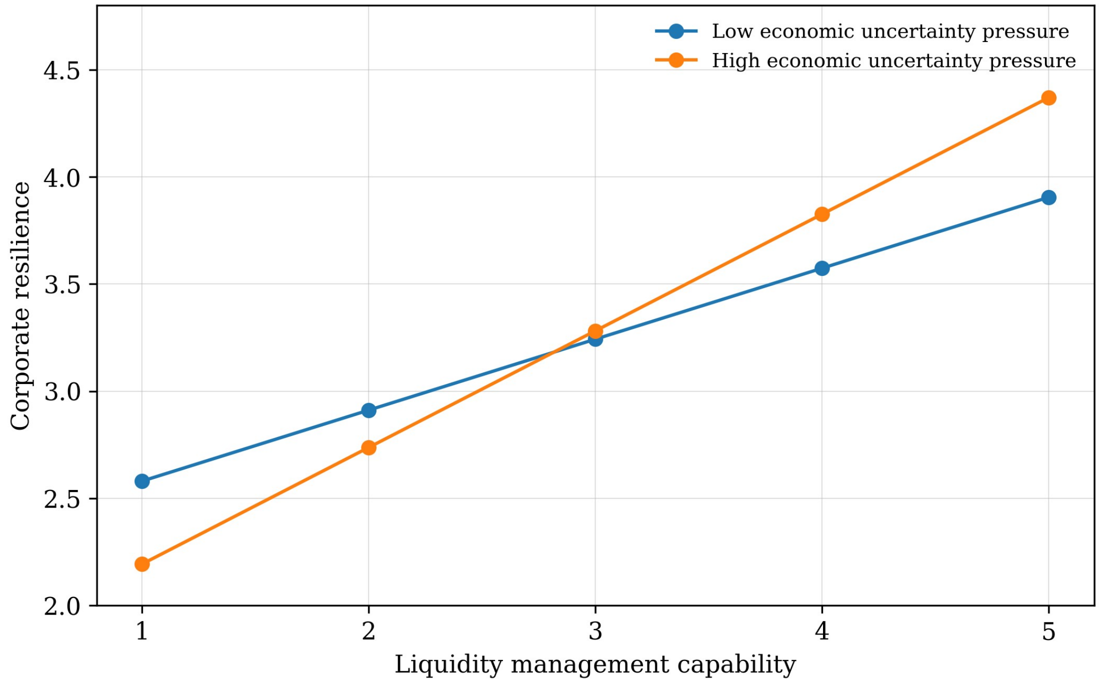

Figure 4. Moderating effect of economic uncertainty pressure on the liquidity-resilience relationship

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The moderation results show that the liquidity management capability is a more binding factor in environments with a high economic uncertainty pressure. The simple slopes for low economic uncertainty pressure were 0.331 and for high economic uncertainty pressure was 0.544. This all helps to build the case that liquidity flexibility is valuable when funding markets for financial firms are skittish, interest rates are volatile, inflation pressures persist and credit can be unreliable. Table 10 presents the statistics for explanatory power, effect sizes, model fit and predictive validity.

Table 10. Explanatory power, effect sizes, model fit, and predictive validity

Endogenous construct	R^2	Adjusted R^2	Q^2_predict
LIQC	0.464	0.462	0.355
CORES	0.612	0.607	0.431

Table 10 continued. Effect sizes

Predictor relationship	f^2
FRMC -> LIQC	0.864
FRMC -> CORES	0.079
LIQC -> CORES	0.198
EUP -> CORES	0.044
LIQC x EUP -> CORES	0.027

Table 10 continued. Model fit indices

Model fit index	Value
SRMR	0.052
d_ULS	0.641
d_G	0.318
NFI	0.914
RMS_theta	0.094

Table 10 continued. PLSpredict results

PLSpredict indicator	PLS-SEM RMSE	Linear model RMSE	Prediction result
CORES1	0.692	0.724	PLS lower
CORES2	0.705	0.731	PLS lower
CORES3	0.681	0.716	PLS lower
CORES4	0.718	0.727	PLS lower
CORES5	0.734	0.729	Linear model slightly lower
Overall result			Medium-to-high predictive validity

The model explained 46.4% of the variance of liquidity management capacity and 61.2% of the variance of corporate resilience. These R^2 values indicate moderate to moderate explanatory power. The hypotheses testing revealed that financial risk management capability has the largest effect size on liquidity management capability ($f^2 = 0.864$). The management of liquidity capability appeared to have a large effect size on corporate resilience, $f^2 = 0.198$. The moderation effect was small, but significant, consistent with norms for interaction effects in behavioural and organizational models (Verma, Narayanan, et al., 2026). SRMR value of 0.052 (acceptable model fit). NFI = 0.914 (adequate global fit). This was complemented by positive Q^2_predict values for both endogenous constructs and a predictive validity assessment of PLSpredict demonstrating that for four out of five corporate resilience indicators, the RMSE generated by PLS-SEM was smaller than the linear

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benchmark (with only one indicator substantially higher), indicating medium-to-high predictive validity (Verma, Rama Murthy, et al., 2026).

7. Discussion, Contributions, and Conclusion

The results show that financial risk management capability directly builds corporate resilience and indirectly through liquidity management capability. The ability to manage financial risk and the ability to maintain liquidity are highly correlated: With the fact that risk governance, stress testing, integrated exposure monitoring, hedging routines as well as timely reporting are providing analytical basis for preparedness regarding liquidities. We also find that liquidity capability is a key pathway to resilience; buffers of liquid assets, cash-flow forecasting, funding diversification, contingency funding planning and matching the maturity of assets and liabilities support the survival of financial firms through shocks and in continuing operations.

This study makes three theoretical contributions. First of all, it combines financial risk management and liquidity management to a corporate resilience framework. Secondly, through the conversion mechanism of risk capability to resilience, through liquidity management capability. Third, it promotes the contingency-based resilience theory by demonstrating that liquidity ability is a more valuable resource with the growing pressure of economic uncertainty. The findings linked a common narrative of financial intermediation theory, enterprise risk management and organizational resilience into a single account of the survival and adaptation strategies employed by financial-firm-suffusion during uncertainty.

In practice, financial firms ideally should consider this management in a broader context as part of their Asset/Liability Management model and not just as a narrow treasury function. Boards and senior executives need to integrate their risk appetite, stress testing, liquidity forecasting, funding diversification and contingency funding processes into a holistic resilience framework. Financial firms also should conduct periodic reviews of whether their liquidity plans remain sufficiently robust as macroeconomic and funding-market conditions evolve over time.

The present study suffers from limitations of cross-sectional survey design and reliance on perceptions. Future studies can use longitudinal data, archival financial indicators, cross-country comparison, or sector-specific models for banks, insurance firms, and NBFCs / Fintech. In sum, this study exemplifies situational financial resilience in the sense that financial resilience in uncertain economic situations depends on the speed of financial risk recognition and management and the degree of liquidity flexibility and adaptive organizational capacity that risk intelligence generates.

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