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Organizational Financial Intelligence Capability: Conceptualization, Scale Development, Validation, And Its RelationshipWith Corporate Performance

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Abstract

Firms acquire more financial data than they convert into effective decisions. We conceptualize Organizational Financial Intelligence Capability (OFIC) as the firm-level capability to acquire, integrate, interpret, diffuse and act upon financial information to reduce uncertainty and equivocality. Organizational information processing theory provides the explanatory foundation, complemented by the dynamic capabilities perspective. Four studies among Indian small and medium-sized enterprises develop and examine a 28-item instrument covering financial data infrastructure, analytical talent, environmental sensing, insight transparency, decision actuation and risk vigilance. Study 2 (n = 318) purifies the instrument; Study 3 (n = 502) supports the six-factor structure (CFI = .968, RMSEA = .040, SRMR = .033), reliability, discriminant validity, sectoral invariance and temporal stability. Study 4 specifies a reflective–formative higher-order construct and identifies positive associations with performance directly and through financial decision quality and access to external finance. Environmental dynamism strengthens the relationship. OFIC adds .147 to explained variance in performance measured six months later beyond four adjacent constructs. The findings distinguish organizational financial capability from individual knowledge and installed technology, while the observational design limits causal interpretation.

Keywords: Organizational financial intelligence capability; scale development; information processing; dynamic capabilities; SMEs; firm performance; PLS-SEM.

1 Introduction

Digital invoicing, automated bank feeds and cloud accounting make financial information increasingly accessible. Yet access does not ensure that firms interpret customer profitability, identify emerging liquidity pressures or use cost information when setting prices. The managerial problem concerns the organizational routines through which financial information becomes a decision. Research on IT, analytics and artificial intelligence capabilities

recognizes this distinction between resources and their productive use (Bharadwaj, 2000; Gupta & George, 2016; Mikalef & Gupta, 2021). Financial information warrants specific attention because it connects operating decisions, externally verified reporting and the assessments made by capital providers.

The existing literature offers incomplete accounts of this competence. Financial literacy resides principally in individuals (Lusardi & Mitchell, 2014), whereas technology-adoption research examines perceptions and intentions preceding capability formation (Jha et al., 2026). Management accounting research identifies useful reporting and control practices but does not necessarily integrate them into a firm-level capability (Davila et al., 2009; Cassar et al., 2015). Consequently, researchers may attribute the same performance difference to owner knowledge, software quality or accounting support without distinguishing their organizational contribution.

We define OFIC as a firm's capability to systematically acquire, integrate, interpret, diffuse and act upon internal and external financial information so as to reduce financial uncertainty and equivocality and convert insight into timely, value-creating decisions. The study asks whether this capability is conceptually distinct, can be measured reliably, and relates to performance through theoretically specified mechanisms. Indian SMEs provide a setting in which expanding financial information infrastructure coexists with substantial differences in managerial routines. Four studies develop the construct, purify and validate its measures, and assess its nomological and incremental predictive validity (Churchill, 1979; MacKenzie et al., 2011; Hulland et al., 2026).

2 Theoretical background and construct specification

2.1 Information processing and organizational capability

Organizational information processing theory explains performance through the fit between information requirements and processing capacity (Galbraith, 1973, 1974; Tushman & Nadler, 1978). Financial decisions create both uncertainty, where necessary information is missing, and equivocality, where managers assign conflicting meanings to available information (Daft & Lengel, 1986). Better data systems can address the first problem, but the second requires communication and shared interpretation. OFIC therefore includes the diffusion and use of insight alongside acquisition and analysis.

This account also predicts contingency. Stable conditions impose relatively predictable information requirements, while volatile prices, credit conditions and demand increase the

value of timely interpretation (Premkumar et al., 2005). The dynamic capabilities perspective complements this mechanism through sensing, seizing and reconfiguring (Teece, 2007). In financial management these processes involve recognizing external signals, committing resources in response to analysis and monitoring exposures as circumstances change. Information processing remains the principal explanatory mechanism; dynamic capabilities clarify its action-oriented dimensions.

2.2 Boundaries and dimensions

OFIC differs from owner-manager financial literacy in its level of analysis: routines can remain effective when particular individuals leave. It differs from general analytics capability in its financial domain, from accounting information system quality in the distinction between a system and its use, and from absorptive capacity in its inclusion of internally generated financial information. Financial position, decision outcomes, personal knowledge and compliance alone are excluded from the construct. A well-capitalized firm need not be financially intelligent, and a sophisticated reporting system may coexist with weak decision routines.

Table 1 The six dimensions of OFIC

Dimension	Organizational content	Items
Financial data infrastructure (FDI)	Integrated, timely, granular and accessible financial data.	5
Financial analytical talent (FAT)	Available expertise for modelling, diagnosis and interpretation, including reliable external advisers.	5
Financial environmental sensing (FES)	Routine monitoring of credit conditions, counterparties, input prices and regulatory change.	4
Financial insight transparency (FIT)	Shared financial understanding across finance and non-financial functions.	5
Financial decision actuation (FDA)	Consistent conversion of analysis into operating and strategic commitments.	5
Financial risk vigilance (FRV)	Controls, early-warning indicators and forward-looking assessment of financial exposure.	4

2.3 Measurement model

Indicators within each dimension are reflective because they manifest a common underlying state and should covary. The dimensions form OFIC because each contributes a distinct organizational function; removing risk vigilance or insight transparency changes the meaning of the construct. Their antecedents can also differ: infrastructure is procured, expertise developed or accessed, and transparency established through communication. Applying Jarvis et al. (2003), OFIC is therefore specified as a Type II reflective–formative higher-order

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construct. Two-stage estimation follows Becker et al. (2012) and Sarstedt et al. (2019). A reflective higher-order alternative is examined as a robustness check rather than selected solely on model fit.

3 Hypothesis development

The fit between financial information requirements and processing capacity should improve resource allocation and performance. **H1:** OFIC is positively associated with SME performance. Better interpretation should first improve the grounding and timing of decisions. **H2:** OFIC is positively associated with financial decision quality. **H3:** Financial decision quality is positively associated with SME performance. **H4:** Financial decision quality mediates the OFIC–performance relationship.

A second mechanism concerns information asymmetry. SMEs often face financing constraints because lenders cannot adequately verify their prospects (Beck & Demirgüç-Kunt, 2006). Credible records, a coherent account of firm economics and monitoring of financial exposure can improve that information environment (Cassar et al., 2015). **H5:** OFIC is positively associated with access to external finance. **H6:** Access to external finance is positively associated with SME performance. **H7:** Access to external finance mediates the OFIC–performance relationship.

Finally, an information processing explanation predicts stronger returns when information requirements rise. **H8:** Environmental dynamism positively moderates the OFIC–performance relationship. Together, these hypotheses specify a direct association, two complementary mediation pathways and a contextual interaction. Firm size, firm age and sector enter as controls.

4 Research design and scale development

4.1 Study 1 Domain specification and item generation

The research sequence combines conceptual specification, item generation, purification, validation and predictive assessment (Churchill, 1979; MacKenzie et al., 2011; Hulland et al., 2026). Exploratory and confirmatory samples are independent. The predictive outcome is measured six months after the capability measures, providing temporal separation without establishing causality.

Deductive item development drew on financial literacy, management accounting, information processing, analytics and SME finance research. Twenty-one semi-structured interviews with Indian SME owner-managers, finance heads and general managers supplemented this

process. Interviews averaged 52 minutes; two researchers coded the material against the six dimensions while allowing additional codes (Cohen's $\kappa = .84$). The interviews highlighted externally accessed expertise and the limited circulation of financial information outside finance departments.

Forty-two firm-referent items were evaluated by nine judges, comprising five academics and four practitioners. Six items failed the content validity ratio threshold of .78 (Lawshe, 1975), leaving 36 items with a scale-level content validity index of .91. Twelve independent judges then sorted items by dimension using the procedure of Moore and Benbasat (1991). The placement ratio was .89 and mean κ was .82. Two items with placement below .70 were removed, yielding 34 items for purification.

4.2 Study 2 Item purification

A survey of 318 Indian SMEs used one knowledgeable owner-manager or finance head per firm, sampled through manufacturing and service industry association directories. Sampling adequacy was satisfactory (KMO = .927; Bartlett's $\chi^2 = 6382.7$, $p < .001$). Parallel analysis using 500 permuted datasets supported six factors (Horn, 1965): six observed eigenvalues exceeded the corresponding 95th-percentile random values, whereas the seventh did not.

Minimum-residual extraction with promax rotation retained indicators loading at least .60 on their intended factor without cross-loadings above .40. FDI6, FAT6, FES5, FIT6, FDA6 and FRV5 were removed. The remaining 28 indicators reproduced six factors explaining 61.06% of common variance, with maximum cross-loading .221 and α between .863 and .897. This preserves the distinction between possessing analytical expertise and routinely applying it to decisions.

5 Study 3 Measurement validation

5.1 Sample and confirmatory analysis

An independent sample of 502 Indian SMEs comprised 284 manufacturing and 218 service firms. The study classified 23 firms as micro, 298 as small and 181 as medium-sized; 215 had a dedicated finance function and 287 did not. No firm appeared in both survey samples. Early and late respondents did not differ significantly on study constructs (all $p > .25$; Armstrong & Overton, 1977). Maximum absolute skewness and kurtosis were .27 and .44, respectively.

Maximum-likelihood confirmatory factor analysis supported six correlated factors: $\chi^2(335) = 597.12$, $\chi^2/df = 1.78$, CFI = .968, TLI = .964, RMSEA = .040, 90% CI [.036, .043], and

SRMR = .033 (Hu & Bentler, 1999). All standardized loadings were significant and ranged from .740 to .855. Table 2 consolidates reliability, convergent validity and temporal stability.

Table 2 Measurement quality by OFIC dimension

Dimension	Loading range	α	CR	AVE	ICC
FDI	.750–.855	.891	.891	.621	.868
FAT	.746–.793	.878	.878	.591	.823
FES	.741–.832	.876	.876	.640	.780
FIT	.743–.838	.885	.886	.609	.878
FDA	.740–.840	.890	.890	.619	.812
FRV	.761–.812	.868	.869	.623	.796

n = 502. CR = composite reliability; AVE = average variance extracted. ICCs use a four-week retest subsample of 96 firms. All loadings $p < .001$; McDonald's ω was within .001 of α.

The square root of AVE exceeded corresponding inter-factor correlations (Fornell & Larcker, 1981), and the largest heterotrait–monotrait ratio was .557, below .85 (Henseler et al., 2015). One-, two- and three-factor models fitted substantially less well (Table 3). The reflective higher-order alternative achieved acceptable fit but a significant deterioration relative to the six-factor model: $\Delta\chi^2(9) = 27.53$, $p = .001$. Its target coefficient was .956 (Marsh & Hocevar, 1985), supporting higher-order representation while leaving the formative specification conceptually preferable.

Table 3 Competing measurement models

Model	χ^2 / df	CFI	RMSEA	SRMR
One factor	4013.34 / 350	.549	.145	.113
Two factors	3435.58 / 349	.620	.133	.104
Three factors	2817.27 / 347	.696	.119	.091
Six correlated factors	597.12 / 335	.968	.040	.033
Reflective higher order	624.65 / 344	.965	.040	.039

5.2 Method bias discriminant validity and invariance

Procedural safeguards included anonymity, randomized item order, different predictor and criterion scale formats, and a later performance measurement (Podsakoff et al., 2003). Harman's first factor explained 24.28% of variance; an unrelated marker variable correlated no more than |.081| with substantive constructs (Lindell & Whitney, 2001); full-collinearity VIFs peaked at 1.87 (Kock, 2015). These diagnostics reduce concern about a dominant common method factor but do not eliminate informant bias.

A 14-construct model combined the six OFIC dimensions, financial decision quality, finance access, performance, dynamism and four adjacent constructs. Fit remained satisfactory:

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$\chi^2(1678) = 2065.87$, CFI = .975, RMSEA = .021, SRMR = .031; maximum HTMT across 91 pairs was .557. Accounting system quality was the closest adjacent construct but remained distinct. Manufacturing and service samples supported configural, metric and scalar invariance. Metric constraints gave $\Delta\chi^2(22) = 20.86$, p = .530; scalar constraints gave $\Delta\chi^2(22) = 27.73$, p = .185. CFI changes were below .01 (Cheung & Rensvold, 2002). Four-week ICCs of .780–.878 support temporal stability.

6 Study 4 Nomological and predictive validity

6.1 Higher order specification and structural results

Study 4 uses the Study 3 sample and its six-month performance follow-up. Two-stage PLS estimation first obtains reflective dimension scores and then uses them as formative indicators, with 5,000 bootstrap resamples and percentile confidence intervals (Becker et al., 2012; Sarstedt et al., 2019; Hair et al., 2022). The maximum formative VIF was 1.75. Weights were positive and significant: infrastructure .398, talent .457, sensing .371, transparency .358, actuation .541 and vigilance .273. Actuation carried the largest estimated weight, although these relative weights should not be interpreted as causal returns to interventions.

Table 4 Structural paths and hypothesis tests

Hypothesis and path	β	p	95% CI
H1 OFIC → performance	.280	< .001	[.191, .378]
H2 OFIC → decision quality	.547	< .001	[.484, .610]
H3 Decision quality → performance	.235	< .001	[.143, .320]
H4 Indirect through decision quality	.129	< .001	[.077, .181]
H5 OFIC → finance access	.383	< .001	[.305, .464]
H6 Finance access → performance	.206	< .001	[.123, .282]
H7 Indirect through finance access	.079	< .001	[.045, .115]
H8 OFIC × dynamism → performance	.103	.006	—
Total OFIC effect on performance	.488	< .001	[.419, .558]

n = 502; 5,000 bootstrap resamples. All eight hypotheses were supported. R^2 = .299 for decision quality, .147 for finance access and .318 for performance. Controls were firm size, firm age and sector.

Both indirect effects exclude zero while the direct association remains significant, indicating complementary partial mediation (Zhao et al., 2010). Decision quality transmits the larger indirect association. The interaction adds .010 to explained variance, with f^2 = .016. Simple slopes increase from .162 at one standard deviation below mean dynamism to .368 above it

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(Aiken & West, 1991). This pattern is consistent with information processing theory, although the interaction is modest and does not rule out other explanations.

6.2 Known groups and incremental prediction

Firms with a dedicated finance function scored higher on OFIC ($t = 8.24$, $p < .001$, Cohen's $d = .73$), with differences on every dimension (all $p < .001$). The finding supports known-groups validity while recognizing that formal finance structures facilitate, rather than define, the capability.

Table 5 Incremental prediction of performance six months later

Step	Predictor set	R^2	ΔR^2
1	Firm size, firm age and sector	.003	—
2	Controls plus financial literacy, analytics capability, accounting system quality and absorptive capacity	.267	.264
3	Step 2 plus OFIC	.414	.147

n = 502. At Step 3, OFIC $\beta = .515$, $p < .001$; F for its incremental contribution = 123.91, $p < .001$. Analytics capability $\beta = .128$, $p < .001$; accounting system quality $\beta = .089$, $p = .029$.

The additional explanatory contribution remains after four plausible competing constructs enter the model. Analytics capability and accounting system quality retain independent associations; financial literacy and absorptive capacity do not in the final specification. This pattern is compatible with organizational routines transmitting some benefits of individual knowledge, but the regression does not itself establish that mediation. Temporal separation strengthens predictive interpretation without resolving reverse causality.

7 Discussion and implications

The findings locate financial intelligence at the organizational level. Financially knowledgeable individuals and capable systems may contribute to OFIC, but neither alone captures whether information is shared and used. The six-dimensional structure identifies different organizational constraints, and the incremental prediction result supports the value of a financial-domain capability alongside more general analytics resources.

The study also extends information processing theory by treating financial equivocality as a coordination problem. Managers can interpret the same margin or cash-flow figure differently because their responsibilities and incentives differ. Insight transparency addresses that interpretive problem, while actuation links understanding to commitment. The positive dynamism interaction is consistent with the expectation that processing capacity becomes more consequential when requirements are volatile.

For managers, diagnosis should precede investment. Data integration addresses weak infrastructure; access to professional advice addresses expertise; cross-functional financial discussion addresses transparency; and explicit decision procedures address actuation. The high actuation weight suggests examining whether analysis influences pricing, purchasing and investment decisions before expanding dashboards. For lenders, the ability to produce and explain credible financial information may complement statement-based assessment. SME support programmes can combine owner training with changes to reporting routines and decision practices rather than assuming that knowledge automatically becomes organizational capability.

8 Limitations and conclusion

The evidence comes from Indian SMEs and a single knowledgeable informant per firm. Sectoral invariance does not establish cross-national invariance, and perceptual performance measures require further comparison with archival outcomes (Wall et al., 2004). Method-bias diagnostics and six-month temporal separation cannot exclude reciprocal effects: successful firms may invest more in systems and expertise. Multi-informant panels, objective forecast or working-capital measures, and credible quasi-experimental variation would strengthen subsequent tests.

The formative specification is theoretically justified but remains sensitive to indicator coverage. Scenario modelling and governance of information access may warrant further conceptual development. Changes in finance automation may also alter the relative contribution of analytical expertise, shared interpretation and actuation. These possibilities call for revalidation rather than assuming permanent stability of the instrument.

Across four studies, OFIC is conceptualized and assessed as a 28-item, six-dimensional organizational capability. The results support reliability, discriminant validity, sectoral invariance, stability and incremental prediction of later performance. Decision quality and access to external finance are complementary pathways, and environmental dynamism strengthens the performance association. The central implication is that financial data create organizational value through established routines of interpretation and action.

Declarations

Competing interests: The authors declare no known competing financial interests or personal relationships that could have appeared to influence this work. **Data availability:** Data and analysis code are available from the corresponding author on reasonable request.

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Appendix A Item diagnostics

Table A1 Retained item distributions and factor loadings

Item	Mean	SD	EFA loading	CFA loading
FDI1	4.68	1.15	0.793	.803
FDI2	4.89	1.14	0.819	.750
FDI3	4.79	1.20	0.720	.760
FDI4	4.26	1.21	0.830	.855
FDI5	4.34	1.17	0.784	.765
FAT1	4.08	1.15	0.772	.793
FAT2	4.84	1.10	0.808	.784
FAT3	4.79	1.16	0.832	.758
FAT4	4.57	1.14	0.628	.760
FAT5	4.39	1.15	0.800	.746
FES1	4.31	1.20	0.840	.827
FES2	4.47	1.21	0.655	.796
FES3	4.52	1.25	0.775	.832
FES4	4.56	1.19	0.657	.741
FIT1	4.83	1.12	0.803	.838
FIT2	4.65	1.10	0.856	.743
FIT3	5.11	1.14	0.743	.746
FIT4	4.30	1.18	0.842	.776
FIT5	4.27	1.21	0.727	.797
FDA1	4.08	1.18	0.810	.807
FDA2	4.08	1.17	0.608	.760
FDA3	4.58	1.14	0.912	.840
FDA4	4.58	1.21	0.774	.740
FDA5	4.91	1.19	0.803	.784
FRV1	4.59	1.16	0.837	.797
FRV2	4.47	1.18	0.769	.812
FRV3	4.34	1.13	0.686	.761
FRV4	4.07	1.20	0.875	.786

EFA: Study 2, n = 318, minimum-residual extraction with promax rotation. CFA and item distributions: Study 3, n = 502. All CFA loadings $p < .001$. The prefixes correspond to the dimensions in Table 1.

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