LEX LOCALIS-JOURNAL OF LOCAL SELF-GOVERNMENT
ISSN:1581-5374 E-ISSN:1855-363X
VOL. 23, NO. 11(2025)

INTEGRATING DISPERSED KNOWLEDGE MANAGEMENT WITH ENTERPRISE RISK AND CRISIS MANAGEMENT: EVIDENCE FROM INDONESIA'S HEAVY EQUIPMENT SECTOR

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Abstract
This study examines how technology and leadership enable dispersed knowledge management (DKM) and how DKM drives operational resilient readiness (ORR)—a KM-grounded indicator of enterprise risk and crisis preparedness—thus integrating DKM with enterprise risk and crisis management in a large multi-site heavy-equipment organization in Indonesia. Cross-sectional employee survey (N = 1,625; Leaders = 485 [29.8%]; Non-Leaders = 1,140 [70.2%]). Reflective PLS-SEM with bootstrapping estimated the model; MICOM and multi-group analysis (MGA) assessed measurement invariance and role-based heterogeneity (Leader vs Non-Leader). The results demonstrate that both technology ($\beta = 0.498$, $p < .001$) and leadership ($\beta = 0.336$, $p < .001$) positively predict DKM, which strongly predicts ORR ($\beta = 0.759$, $p < .001$). The model explains 59.6% of DKM and 57.7% of ORR. MGA indicates no significant path differences between Leaders and Non-Leaders, suggesting role-invariant mechanisms. Cross-sectional, self-reported data; future studies should triangulate with incident/BCP records and track resilience longitudinally or across events. Strengthening the technology backbone and leadership micro-practices that mobilize knowledge across sites can raise crisis readiness consistently across roles; embed DKM routines (briefings, after-action reviews, cross-site communities) in ERM/BCP playbooks. Provides large-sample evidence from an asset-intensive, emerging-market setting showing that DKM is the mechanism through which organizational enablers (technology, leadership) drive operational resilience, with effects that generalize across role groups.

Keywords: Dispersed Knowledge Management; Operational Resilience; Enterprise Risk Management; Crisis Management; Heavy Equipment; Multi-Group Analysis.

Introduction

Organizations with geographically dispersed operations face recurrent shocks ranging from supply-chain turbulence and safety incidents to extreme weather, making the orchestration of knowledge flows across sites central to continuity and performance (Duchek, 2020; Hillmann, 2021). We examine how dispersed knowledge management (DKM) connects to operational resilience in a large multi-site heavy-equipment organization in Indonesia. Recent reviews emphasize resilience's growing salience but also conceptual fragmentation, underscoring the need to specify mechanisms that translate knowledge into day-to-day readiness (Duchek, 2020; Hillmann, 2021).

We conceptualize dispersed knowledge management (DKM) as the deliberate coordination of knowledge creation, sharing, and reuse across locations, roles, and functions—beyond single-site boundaries. Earlier studies on knowledge ecosystems suggest that coordinating distributed knowledge is crucial for sustaining continuity and performance, although the underlying operational mechanisms are still under-ecplained (Gomes et al., 2021). Linking DKM to enterprise risk management (ERM) and crisis management requires an operational outcome that captures preparedness and adaptive response; we therefore use operational resilient readiness (ORR) as an indicator of ERM/crisis preparedness at the field-operations level (Duchek, 2020; Hillmann, 2021).

Two organizational enablers are particularly salient. Technology (e.g., digital platforms, collaboration tools, telemetry/telematics, knowledge repositories) provides the backbone for capturing and mobilizing knowledge across distance; leadership shapes climates and routines (goal alignment, after-action reviews, coaching) that sustain sharing and reuse. Empirical scholarship documents how leadership support and technology-enabled arrangements facilitate intra-organizational knowledge sharing and learning conditions that plausibly scale in dispersed operations (Castaneda and Durán, 2018; Gomes et al., 2021).

Against this backdrop, we address three gaps. First, much KM research links knowledge to aggregate performance rather than to resilience-oriented outcomes central to ERM/crisis programs (Hillmann, 2021). Second, studies of dispersed (multi-site) knowledge processes where the distance between knowledge supply and demand is physical, temporal, and organizational remain scarce in asset-intensive settings (Gomes et al., 2021). Third, we know little about role invariance: do the same pathways operate similarly for Leaders and Non-Leaders, who differ in decision rights and information access? Addressing these gaps advances the integration of KM with risk/crisis scholarship and informs how firms should design organization-wide interventions.

We test a reflective PLS-SEM model in which Technology and Leadership predict DKM, which in turn predicts ORR. To ensure valid cross-group comparisons, we establish measurement invariance using the MICOM procedure and then examine role-based heterogeneity with multi-group analysis (MGA). Following best practice, we implement MICOM's three-step approach, configural, compositional, and equality of means/variances within a permutation framework prior to MGA comparisons (Henseler et al., 2016; SmartPLS Documentation).

Our study is guided by the following research questions:

1. RQ1: How do Technology and Leadership enable Dispersed KM in a multi-site heavy-equipment context?
2. RQ2: To what extent does Dispersed KM enhance Operational Resilience Readiness (as an indicator of ERM/crisis preparedness)?
3. RQ3: Are these relationships role-invariant, i.e., do they hold similarly for Leaders and Non-Leaders?

This paper contributes in three ways. First, it provides large-sample evidence tying dispersed KM to a resilience-oriented outcome, advancing the integration of KM with ERM/crisis scholarship (Duchek, 2020; Hillmann, 2021). Second, it quantifies the relative effects of Technology and Leadership as complementary enablers of DKM in dispersed operations (Gomes et al., 2021). Third, by establishing measurement invariance and demonstrating no significant cross-role differences in structural paths, it suggests that organizations can pursue role-agnostic (organization-wide) interventions to strengthen readiness (Henseler et al., 2016).

Theoretical background and hypotheses Development

1. Dispersed knowledge management (DKM) and operational resilient readiness (ORR)

   Organizational resilience research highlights preparedness and adaptive capacity as core to withstanding and recovering from disruptions; conceptually, resilience unfolds through anticipation, coping and adaptation capabilities (Duchek, 2020; Hillmann, 2021). We position operational resilient readiness (ORR) as an operational-level indicator of enterprise risk/crisis preparedness that reflects the ability of frontline units to sense, respond and learn in the face of incidents. In distributed operations, such readiness depends on how effectively knowledge is created, mobilized and reused across sites and roles—what we call dispersed knowledge management (DKM). Earlier studies on knowledge ecosystems suggest that coordinating distributed knowledge is crucial for sustaining continuity and performance, although the underlying operational mechanisms are still under-explained (Gomes et al., 2021).

2. Technology as an enabler of dispersed KM

Technology provides the backbone for capturing, codifying and moving knowledge across spatial and temporal boundaries—through repositories, collaboration platforms and telemetry/analytics infrastructure (Alavi and Leidner, 2001). In dispersed settings, such infrastructure lowers search and transfer costs and makes cross-site reuse feasible; evidence in JKM also shows that technology-enabled arrangements help focal firms orchestrate knowledge flows with heterogeneous actors. We therefore expect stronger DKM where technology enablement is higher.

H1. Technology positively influences dispersed knowledge management (DKM). (Alavi and Leidner, 2001; Gomes et al., 2021).

3. Leadership as an enabler of dispersed KM

Leadership shapes the climates and routines that sustain knowledge sharing and learning—e.g., goal alignment, after-action reviews and coaching—thereby enabling knowledge to cross functional and site boundaries. Empirical research links knowledge-oriented leadership to stronger KM practices and downstream outcomes, suggesting leaders' pivotal role in fostering sharing and reuse. We thus expect leadership to strengthen DKM.

H2. Leadership positively influences dispersed knowledge management (DKM). (Donate and de Pablo, 2015).

4. From dispersed KM to operational resilient readiness

Resilience capabilities depend on timely access to relevant knowledge during disruptions; by increasing availability and usefulness of cross-site know-how, DKM should raise operational readiness to anticipate, absorb and adapt.

H3. Dispersed knowledge management (DKM) positively influences operational resilient readiness (ORR). (Duchek, 2020; Hillmann, 2021).

5. Cross-role generalisability and the need for invariance testing

Before comparing structural paths across Leaders versus Non-Leaders, measurement invariance must be established. We follow the MICOM procedure—configural, compositional and equality of means/variances—implemented via permutation, which is the recommended approach for composite (PLS-SEM) models prior to multi-group analysis (MGA). Our cross-role comparison is therefore framed as an empirical question contingent on MICOM. RQ. Do the structural relationships generalise across role groups (Leaders vs Non-Leaders) once measurement invariance is established via MICOM? (Henseler et al., 2016).

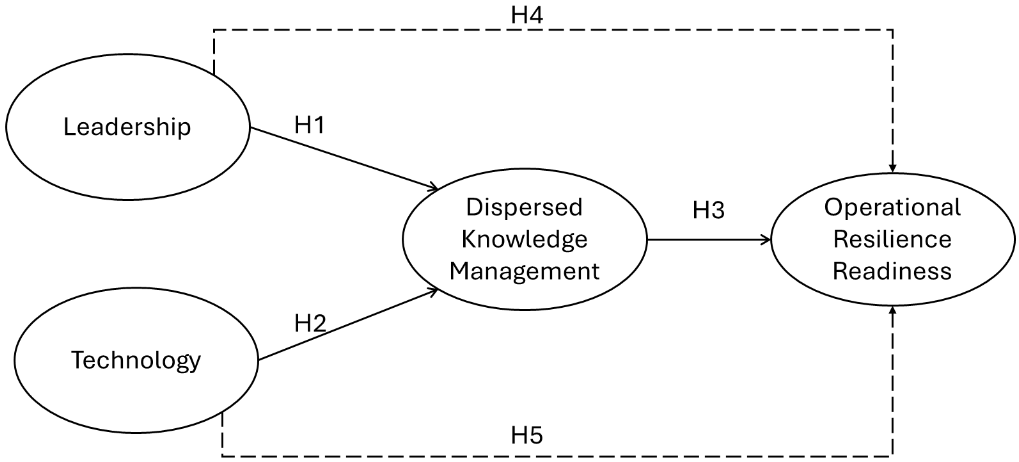

Fig. 1 Conceptual Framework of the Study

Research Methodology

1. Research design and context

We employ a cross-sectional survey to examine how Technology and Leadership enable Dispersed Knowledge Management (DKM), which in turn relates to Operational resilience readiness (ORR) in a large multi-site heavy-equipment organization in Indonesia. The setting involves geographically dispersed operations (e.g., field service, maintenance, logistics, safety), where coordinating knowledge across sites is mission-critical for continuity. Contextual information about risk governance, crisis/BCP arrangements, and digital enablement is drawn from publicly available corporate disclosures (e.g., sustainability and annual reporting for the study period).

2. Sample and data collection

Data were collected from 1,625 employees across multiple business units and locations (84 operational sites in 34 provinces of Indonesia). Participation was voluntary and anonymous, with informed consent before response. For multi-group analysis (MGA), we use position as the grouping variable (Leaders vs Non-Leaders). Cases with excessive missingness on focal constructs were excluded before model estimation. The final analytic dataset contains complete records on all measurement items used in the PLS-SEM analysis.

3. Measures

All focal constructs are modelled as reflective and measured using multi-item Likert-type indicators adapted from prior literature (wording and codes reported in the tables/appendix). Dispersed Knowledge Management (DKM) captures cross-site knowledge creation, sharing, and reuse; Technology reflects digital infrastructure and tools that support knowledge capture and collaboration; Leadership reflects behaviours/routines that enable knowledge sharing and learning (e.g., goal alignment, briefings/debriefs); ORR captures operational readiness to anticipate, respond, and learn during disruptions. Item purification followed standard psychometric practice (indicator loadings, reliability, and validity checks) before structural estimation (Hair et al., 2021).

4. Estimation approach: PLS-SEM

We use partial least squares structural equation modelling (PLS-SEM) to estimate the measurement and structural models, given the study's prediction-oriented aim, composite measurement, and the multi-construct, multi-group design (Hair et al., 2021; Hair, 2022). Non-parametric bootstrapping is applied to obtain standard errors and confidence intervals for path estimates. Model estimation and resampling are conducted in SmartPLS.

Measurement quality. Convergent validity is assessed via indicator loadings and average variance extracted (AVE ≥ 0.50); internal consistency via Cronbach's α, rho_A, and composite reliability (CR) following established thresholds (Hair et al., 2021). Discriminant validity is assessed using the heterotrait–monotrait ratio (HTMT) with its inference procedure (Henseler et al., 2015; SmartPLS documentation), adopting conservative cut-offs (e.g., HTMT < 0.85/0.90) and confidence intervals not crossing 1. Collinearity is screened via VIF for outer and inner models, retaining values within accepted limits for PLS path modelling. Approximate model fit is reported using SRMR for saturated and estimated models, as recommended for variance-based SEM when used cautiously and alongside other criteria (Hair et al., 2021).

Explanatory/predictive assessment. We report R2 (and Radj2) for endogenous constructs to gauge explained variance and, where applicable, blindfolding (Q2 redundancy) to indicate predictive relevance (Hair et al., 2021). Where warranted, PLS-Predict can complement in-sample metrics with out-of-sample prediction diagnostics.

5. Measurement invariance and multi-group analysis

Prior to any cross-group comparison, we assess measurement invariance using the MICOM procedure (Henseler, Ringle, and Sarstedt, 2016), implemented via permutation in SmartPLS. MICOM comprises: (i) configural invariance (identical model specification, indicators, data treatment), (ii) compositional invariance (correlation c ≈ 1 across groups), and (iii) equality of composite means/variances. Only after establishing (at least) partial invariance do we proceed to MGA to test for differences in structural paths between Leaders and Non-Leaders (Henseler et al., 2016; SmartPLS documentation).

Result and Discussion

1. Measurement model

All primary indicators load strongly on their intended constructs.

Table 1. Outer Loadings of Reflective Indicators

Indicator	Construct	Outer Loading
KM1	Dispersed KM	0,800
KM2	Dispersed KM	0,827
KM3	Dispersed KM	0,786
KM4	Dispersed KM	0,858
KM5	Dispersed KM	0,853
L1	Leadership	0,811
L2	Leadership	0,844
L3	Leadership	0,835
L4	Leadership	0,820
L5	Leadership	0,809
ORR1	Operational Resilience Readiness	0,770
ORR2	Operational Resilience Readiness	0,847
ORR3	Operational Resilience Readiness	0,860
ORR4	Operational Resilience Readiness	0,872
ORR5	Operational Resilience Readiness	0,834
ORR6	Operational Resilience Readiness	0,724
T1	Technology	0,864

T2	Technology	0,908
T3	Technology	0,828
T4	Technology	0,883

Note: Only indicators with loadings ≥ 0.70 were considered strong.

The lowest loading is ~0.72, and the remainder meet the ≥0.70 guideline. Reliability and convergent validity are satisfactory.

Table 2. Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability	Rho_A	AVE
Dispersed KM	0,883	0,914	0,886	0,681
Leadership	0,882	0,914	0,882	0,679
Operational Resilience Readiness	0,901	0,924	0,904	0,672
Technology	0,894	0,926	0,899	0,759

Cronbach's α, rho_A, and composite reliability exceed recommended thresholds, and AVE is ≥0.50 for all constructs. Discriminant validity is supported: HTMT values are below conservative cut-offs, and the associated 95% confidence intervals do not include 1.

Table 3. Heterotrait–Monotrait Ratio (HTMT) for Discriminant Validity

Relationship	HTMT	Sample Mean	CI 2.5%	CI 97.5%	Discriminant Validity
Leadership <-> Dispersed KM	0,776	0,777	0,743	0,808	Yes
Operational Resilience Readiness <-> Dispersed KM	0,847	0,847	0,820	0,873	Yes
Operational Resilience Readiness <-> Leadership	0,725	0,725	0,690	0,757	Yes
Technology <-> Dispersed KM	0,823	0,823	0,793	0,851	Yes
Technology <-> Leadership	0,783	0,783	0,750	0,813	Yes
Technology <-> Operational Resilience Readiness	0,777	0,777	0,746	0,807	Yes

Note: All HTMT values are below the critical threshold of 0.90, with confidence intervals not containing 1.0, indicating adequate discriminant validity across constructs (Henseler et al., 2015).

2. *Collinearity (outer/inner)*

Collinearity diagnostics indicate no issues. All reported VIF values are below the conservative 3.3 threshold.

Table 4. Collinearity (Outer VIF)

Indicator	VIF
KM1	1,998
KM2	2,270
KM3	1,901
KM4	2,870
KM5	2,795
L1	2,154
L2	2,486
L3	2,244
L4	2,062
L5	1,926
ORR1	1,907
ORR2	2,482
ORR3	2,731
ORR4	2,986
ORR5	2,431
ORR6	1,597
T1	2,386
T2	3,097
T3	2,089
T4	2,600

Table 5
Model Fit (SRMR)

Model	SRMR
Saturated model	0,047
Estimated model	0,067

Table 6
Collinearity (Inner VIF)

Predictor Path	VIF
Dispersed KM -> Operational Resilience Readiness	1,000
Leadership -> Dispersed KM	1,950
Technology -> Dispersed KM	1,950

3. *Structural model (H1–H3)*
   Bootstrapping results support all hypothesised relationships.

Table 7. Structural Model – Path Coefficients and Significance

Path	Coefficient (β)	T-Statistic	P-Value	Significance
Dispersed KM -> Operational Resilience Readiness	0,759	58,400	0,000	Significant
Leadership -> Dispersed	0,336	13,036	0,000	Significant

KM				
Technology -> Dispersed KM	0,498	19,769	0,000	Significant

Technology positively predicts DKM (H1: $\beta = 0.498$, $p < .001$), and Leadership positively predicts DKM (H2: $\beta = 0.336$, $p < .001$). DKM, in turn, positively predicts ORR (H3: $\beta = 0.759$, $p < .001$). The corresponding 95% confidence intervals do not straddle zero, confirming statistical significance.

Effect sizes indicate a moderate effect of Technology on DKM ($f^2 \approx 0.315$), a weak-to-moderate effect of Leadership on DKM ($f^2 \approx 0.143$), and a strong effect of DKM on ORR ($f^2 \approx 1.363$).

Table 8. Coefficient of Determination (R^2)

Endogenous Construct	R^2
Dispersed KM	0,596
Operational Resilience Readiness	0,577

4. Explanatory power and predictive relevance

The model explains substantial variance in the endogenous constructs (Table VII): R^2(DKM) = 0.596 and R^2(ORR) = 0.577. In addition, cross-validated predictive relevance assessed with PLSpredict is strong:

Table 9. Indirect Effect

Indirect Path	β_indirect	STDEV	T Values	P Values
Leadership -> Dispersed KM -> Operational Resilience Readiness	0,255	0,020	12,845	0,000
Technology -> Dispersed KM -> Operational Resilience Readiness	0,379	0,022	17,434	0,000

Q^2predict for Dispersed KM (DKM) = 0.594 and for Operational Resilience Readiness (ORR) = 0.515, both above the 0.35 "large" threshold, indicating meaningful out-of-sample predictive capability.

5. Indirect and total effects (H4–H5)

Specific indirect effects via DKM are significant:

Table 10. Indirect Effect

Indirect Path	β_indirect	STDEV	T Values	P Values
Leadership -> Dispersed KM -> Operational Resilience Readiness	0,255	0,020	12,845	0,000
Technology -> Dispersed KM -> Operational Resilience Readiness	0,379	0,022	17,434	0,000

Leadership → DKM → ORR supports H4, and Technology → DKM → ORR supports H5. Total effects (Table X) align with DKM acting as the transmission mechanism from organizational enablers to ORR.

6. Measurement invariance and multi-group analysis

MICOM (permutation) confirms compositional invariance for all constructs (Step 2; p_perm ≥ .05: Dispersed KM = .3646; Leadership = .6634; Operational Resilient Readiness = .9954; Technology = .7884), thereby establishing partial measurement invariance and permitting MGA.

Table 11. MICOM Step 2 Compositional Invariance (Permutation)

Groups compared	Construct	c (original)	c (perm. mean)	5% quantile	p-value	Decision
Leader vs Non-Leader	Dispersed KM	0.9999	0.9999	0.9998	0.3646	Invariance supported
Leader vs Non-Leader	Leadership	0.9999	0.9998	0.9996	0.6634	Invariance supported
Leader vs Non-Leader	Operational Resilience Readiness	1.0000	0.9999	0.9997	0.9954	Invariance supported
Leader vs Non-Leader	Technology	1.0000	0.9999	0.9998	0.7884	Invariance supported

Note: Compositional invariance is supported when the permutation p-value ≥ 0.05 (fail to reject H0: c = 1).

Table 12. MICOM Step 3b Equality of Composite Variances

Groups compared	Construct	Δ var (orig)	Δ var (perm. mean)	2.5% quantile	97.5% quantile	p-value	Decision
Leader vs Non-Leader	Dispersed KM	-0.0608	-0.0012	-0.1458	0.1438	0.4128	Equal (supported)
Leader vs Non-Leader	Leadership	0.0299	-0.0014	-0.1509	0.1473	0.6910	Equal (supported)
Leader vs Non-Leader	Operational Resilience Readiness	0.0355	-0.0012	-0.1380	0.1360	0.6178	Equal (supported)
Leader vs Non-Leader	Technology	0.0479	-0.0018	-0.1457	0.1389	0.4828	Equal (supported)

Note: Equality of composite variances is supported when the permutation p-value ≥ 0.05 (fail to reject difference).

In Step 3, equality of composite means is supported for Dispersed KM (p = .9704), Leadership (p = .5288), and Technology (p = .0736), but not for Operational Resilience Readiness (p = .0278); equality of composite variances is supported for all constructs (all p_perm ≥ .41). Based on these preconditions, the MGA results

Table 13. MGA (Leader vs Non-Leader): Path Coefficients

Path	β Leader	β Non-Leader	Δβ	P Values
Dispersed KM -> Operational Resilience Readiness	0,770	0,757	0,013	0,640
Leadership -> Dispersed KM	0,323	0,342	-0,019	0,744
Technology -> Dispersed KM	0,504	0,497	0,007	0,893

Show no significant group differences in structural paths between Leaders and Non-Leaders (all p_perm > .05)—for example, DKM → ORR: $\Delta\beta = 0.013$, $p = .640$; Leadership → DKM: $\Delta\beta = -0.019$, $p = .744$; Technology → DKM: $\Delta\beta = 0.007$, $p = .893$. Consistently, group-wise explanatory power is comparable, with non-significant differences in R^2 (DKM: $\Delta R^2 = -0.027$, $p = .511$; ORR: $\Delta R^2 = 0.020$, $p = .638$).

Table 14. MGA (Leader vs Non-Leader): Coefficient of Determination (R^2)

Endogenous Construct	β Leader	β Non-Leader	Δβ	P Values
Dispersed KM	0,578	0,605	-0,027	0,511
Operational Resilience Readiness	0,593	0,573	0,020	0,638

Discussion

Summary of findings

This study set out to explain how organizational enablers translate into operational resilient readiness (ORR) through dispersed knowledge management (DKM) in a multi-site heavy-equipment context. The results show that Technology and Leadership both positively predict DKM (supporting H1–H2), and that DKM in turn positively predicts ORR (supporting H3). The specific indirect effects from Technology and Leadership to ORR via DKM are significant (supporting H4a–H4b), indicating that DKM functions as the mechanism linking organizational enablers to readiness. Measurement invariance is established (MICOM), and multi-group analysis (MGA) reveals no significant path differences between Leaders and Non-Leaders; the structural relations therefore generalize across roles.

Theoretical implications

First, the findings extend resilience research by specifying DKM as the capability conduit through which enablers shape operational readiness. Prior resilience work emphasizes anticipation, coping, and adaptation (Duchek, 2020; Hillmann, 2021); our evidence shows that these capabilities are materially supported when cross-site knowledge is systematically captured, mobilized, and reused. Second, the results differentiate enablers: technology provides the infrastructure for cross-site access and reuse (e.g., repositories, collaboration, telemetry/analytics), whereas leadership sustains the routines and climate that keep knowledge flowing (e.g., briefings, after-action reviews, coaching) (Alavi and Leidner, 2001; Donate and de Pablo, 2015). Positioning both as complementary inputs clarifies why KM programmes that focus on tools without behaviors—or vice versa—often underperform. Third, role-invariant pathways suggest that the central logic of "enablers → DKM → ORR" is organization-wide rather than role-contingent. This adds nuance to dispersed-knowledge research in complex ecosystems (Gomes et al., 2021), indicating that once a common technological and leadership scaffolding is in place, the benefits of DKM travel across hierarchical levels.

Managerial implications

For managers responsible for risk and crisis preparedness, the results imply that raising ORR is most effectively approached by designing and governing DKM. Practically, this means (i) investing in a technology backbone that lowers search and transfer costs across sites (platforms for collaboration, codified repositories, telemetry/telematics that surface anomalies and lessons learned), and (ii) institutionalizing leadership micro-practices that keep knowledge circulating (goal alignment, pre-task briefings, post-incident reviews, coaching for sharing). Because effects are role-invariant, these interventions can be rolled out uniformly across Leaders and Non-Leaders, with adaptation only to local workflows. Critically, firms should embed DKM routines into ERM/BCP playbooks—for example, by hard-wiring after-action learning cycles, cross-site communities of practice, and rapid dissemination of corrective actions into incident management processes. Doing so converts knowledge flows into repeatable, auditable risk routines that strengthen day-to-day readiness.

Robustness and boundary conditions

The study follows contemporary PLS-SEM practice, reports measurement quality (loadings, reliability, AVE, HTMT), checks collinearity and approximate fit (SRMR), and establishes measurement invariance before MGA—mitigating common validity threats in group comparisons. Nonetheless, several boundary conditions apply. The design is cross-sectional and relies on self-reports; future work should triangulate with incident logs, BCP exercises, ERM maturity assessments, and objective performance. The context is a single heavy-equipment organization in an emerging market; replication across industries, countries, and different types of shocks (e.g., supply chain vs. safety vs. climate events) would strengthen generalisability. Finally, while our model emphasizes a mediated pathway through DKM, subsequent research could compare partial versus full mediation by adding direct links from enablers to ORR, and could examine temporal dynamics (e.g., how DKM and ORR co-evolve following major incidents).

Conclusion

This study explains how organizational enablers translate into operational resilient readiness (ORR) through dispersed knowledge management (DKM) in a large, multi-site heavy-equipment organization in Indonesia. The evidence shows that technology and leadership both foster DKM, and that DKM, in turn, strengthens ORR. Establishing measurement invariance and finding no role-based differences in the structural paths indicate that these relationships generalize across Leaders and Non-Leaders. Theoretically, the model clarifies DKM as the capability conduit linking enablers to resilience-oriented readiness and, in doing so, advances the Special Issue's integration agenda across knowledge management, enterprise risk management, and crisis management.

The findings carry clear managerial implications. Raising crisis and risk preparedness is best approached by designing and governing DKM rather than by isolated tools or training initiatives. Managers should build the technology backbone that lowers search and transfer costs across sites (collaboration platforms, knowledge repositories, analytics/telematics) and institutionalize leadership micro-practices that keep knowledge circulating (goal alignment, briefings and debriefs, after-action reviews, coaching for sharing). Because effects are role-invariant, these interventions can be deployed organization-wide and embedded directly into ERM and business-continuity playbooks, turning knowledge flows into repeatable, auditable risk routines.

Several limitations bound the contributions. The design is cross-sectional and relies on self-reported perceptions, which constrains causal inference and may not fully capture how readiness unfolds during actual incidents. The study focuses on a single organization in an asset-intensive, emerging-market context; generalizability to other industries and institutional settings should be assessed. ORR is operationalized as an indicator of ERM/crisis preparedness at the operational level; alternative operationalizations may reveal complementary facets of readiness. Although measurement invariance was established before multi-group comparisons, unobserved heterogeneity or omitted contextual moderators (e.g., site digitalization intensity, incident exposure) may still shape local outcomes.

Future research can deepen and broaden these insights in several ways. Longitudinal or event-based designs could track how DKM and ORR co-evolve before, during, and after disruptions, including the durability of improvements following major incidents. Multi-source, multi-level studies that combine survey data with incident logs, BCP exercise results, ERM maturity assessments, and objective performance indicators would strengthen causal claims and reduce common-method concerns. Comparative studies across industries and countries could identify boundary conditions and institutional contingencies for the enablers → DKM → ORR pathway. Model extensions might examine partial versus full mediation by adding direct links from enablers to ORR, incorporating additional enablers (e.g., organizational design or social capital), and testing moderators such as digitalization intensity, geographical dispersion, or network structure of knowledge flows. Finally, predictive-validity assessments using out-of-sample procedures can complement explanatory metrics and clarify how well the model anticipates readiness across varied operating conditions.

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