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Network Prioritization of Factors Shaping Knowledge Acquisition Using a Hybrid DEMATEL-ANP Approach: Expert Judgments from Iran's Marine Sector

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ABSTRACT

This study maps expert-perceived interdependencies and priorities among factors associated with knowledge acquisition in Iran's marine sector, where distributed operations, personnel mobility, and safety-critical tasks make systematic knowledge capture strategically important. Using a hybrid DEMATEL-based analytic network process (DANP), the analysis draws on 20 individual direct-influence matrices supplied by experts in marine operations, safety management, ship operations, and academia. The criterion framework links organizational capabilities as opportunity conditions, the theory of planned behavior as a motivational gateway, and SECI as a knowledge-conversion lens across six clusters and 20 sub-criteria. Behavioral factors receive the highest cluster priority, closely followed by organizational culture, information technology, and learning conditions. In the aggregated expert-judgment network, perceived behavioral control, attitude, subjective norms, recognition of knowledge value, management practices, strategic alignment, and IT infrastructure occupy cause-side positions, whereas supportive culture is high-priority but effect-side. Reward priorities are close: personal growth and reputation have near-identical point estimates and both rank above cash rewards within this expert panel, but the small gaps do not establish a universal reward hierarchy. Priority rankings remain highly consistent under median and 10% trimmed-mean aggregation; median aggregation changes the cause-side/effect-side classification of only three sub-criteria with near-neutral directional positions, whereas all directional classifications remain unchanged under leave-one-expert-out analysis. Experts show stronger concordance for outgoing than incoming influence rankings. The study distinguishes theoretical relevance, network priority, and directional position, and supports context-sensitive pilot interventions rather than universal causal prescriptions.
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1. Introduction

Knowledge acquisition matters in marine organizations because operational knowledge is dispersed across vessels, shore offices, regulators, contractors, and transient crews. Mobility can remove experience, while ship-shore separation can prevent available knowledge from reaching recipients. Fei (2011) shows that information technology, sharing culture, and leadership preserve and transfer expertise during employee mobility. These are adjacent flow mechanisms: they matter here only when they make knowledge available for recipient acquisition. Accident-report knowledge likewise reaches officers through employers, training materials, media, and peers (Mallam *et al.*, 2022), while language and informal relations shape discussion of work problems in multilingual crews (Pauksztat, 2021). Maritime knowledge clusters can support performance through social capital and absorptive capacity (Zhou *et al.*, 2021). Together, these studies identify organizational conditions for obtaining and interpreting distributed knowledge.

These conditions make marine knowledge acquisition consequential in three connected domains. Economically, failures to capture and reuse knowledge can increase rework, downtime, training costs, and dependence on scarce specialists. Recent shipping evidence links technological and organizational learning resources with innovation capability and, through innovation, with organizational resilience and competitiveness (Li *et al.*, 2024). Environmentally, systematic knowledge capture supports learning about more sustainable maritime operations (Kuznetsov *et al.*, 2017). Societally, the quality of organizational learning influences the ability of frontline personnel to recognize hazards, communicate problems, and learn from incidents (Mallam *et al.*, 2022; Pauksztat, 2021). Digital infrastructures can

also structure maritime accident knowledge for storage, querying, and reasoning, as demonstrated by a knowledge graph built from 581 accident reports (Liu & Cheng, 2024).

Prior knowledge-management (KM) research places acquisition within creation, storage or retrieval, transfer, and application (Alavi & Leidner, 2001; Gold *et al.*, 2001), but does not establish a context-independent ordering of its enabling conditions. Nguyen *et al.* (2019) find that intrinsic and extrinsic motivations relate to knowledge sharing and vary across individual, organizational, and cultural contexts. Because sharing makes knowledge available rather than demonstrating recipient uptake, this evidence informs conditions surrounding acquisition but does not directly validate acquisition effects. Accordingly, the study examines rewards, culture, technology, and behavior as interdependent conditions in the marine setting. Survey evidence also cautions against assuming a direct performance effect: Fathi *et al.* (2021) found that structured knowledge was associated with organizational outcomes, whereas the direct knowledge-acquisition path to organizational performance was not statistically significant. This contrast supports treating acquisition as one stage whose consequences depend on conversion, application, and context.

The study addresses these interdependencies through a theory-informed expert network analysis in Iran's marine sector. The framework links three analytically distinct layers: organizational capabilities define the opportunity and resource context, the theory of planned behavior (TPB) specifies the motivational gateway to deliberate knowledge seeking and acceptance, and socialization-externalization-combination-internalization (SECI) provides a conversion lens for making acquired knowledge interpretable and usable. The

DEMATEL-based analytic network process (DANP) maps perceived interdependencies across these layers and derives network-adjusted priorities from the aggregate direct-influence matrix. Therefore, the central research question is: How do marine-sector experts perceive the interdependencies and relative priorities among motivational and organizational factors associated with knowledge acquisition in Iranian marine organizations?

The study contributes by (1) differentiating knowledge acquisition from adjacent KM processes; (2) articulating an opportunity-motivation-conversion mechanism that links organizational capabilities, TPB, and SECI without treating them as a tested causal model; (3) reporting full-system and within-cluster DEMATEL results separately; (4) deriving priorities through a cluster-weighted DANP supermatrix; and (5) jointly interpreting prominence, net directional position, priority, observed expert agreement, LOEO robustness, and aggregation-rule sensitivity without treating these outputs as evidence of empirical causation.

2. Theoretical background

2.1 Knowledge acquisition and adjacent KM processes

Conceptual precision matters because acquisition, creation, sharing, transfer, and utilization are related but not interchangeable. Knowledge acquisition refers here to obtaining knowledge from internal or external sources so that it becomes available to an individual or organization; it precedes, but does not by itself guarantee, conversion, storage, transfer, or application. Huber (1991) treats acquisition as a contributing process of organizational learning, while Gold *et al.* (2001) position acquisition as a KM process capability.

Knowledge creation concerns the development of new knowledge through recurring interaction between tacit and

explicit forms (Nonaka, 1994); newly created knowledge may subsequently be acquired by other actors. Knowledge sharing emphasizes an individual's willingness and behavior in making knowledge available directly or through a repository (Bock *et al.*, 2005; Wang & Noe, 2010). Sharing can occur without demonstrated recipient change, whereas knowledge transfer is evidenced when one unit's experience affects another unit (Argote & Ingram, 2000).

Knowledge utilization or application refers to using accessible and interpreted knowledge in decisions, routines, or task performance. It is analytically downstream from making knowledge available, although feedback from use can initiate further acquisition and creation. This boundary follows the process view of KM in which creation, storage/retrieval, transfer, and application are distinguishable but interdependent activities (Alavi & Leidner, 2001). Evidence from digital product-development teams further indicates that knowledge comprehension, documentation, and dissemination can mediate the progression from external knowledge acquisition to knowledge exploitation and transformation (Erhan *et al.*, 2024).

2.2 Why the marine context matters

Marine work combines mobility, distributed operations, hierarchical coordination, safety-critical tasks, multilingual interaction, and changing regulation. Fei (2011) treats mobility as both knowledge loss and a knowledge-flow channel when information technology, leadership, and sharing culture are present. Pauksztat (2021) shows that language diversity shapes informal problem communication, while Mallam *et al.* (2022) show that officers obtain accident knowledge from formal reports, adapted materials, employers, media, and peers. These studies examine flow, communication, and learning

channels rather than acquisition alone. They are relevant because they explain how knowledge becomes available and accessible to a recipient: the boundary used here for acquisition.

The context therefore changes the value of acquisition mechanisms. A technically sophisticated repository is insufficient when connectivity, accessibility, trust, language, time, or managerial practices prevent use. Liu and Cheng (2024), for example, show the technical potential of a maritime accident knowledge graph, but such infrastructure still depends on organizational routines that make stored knowledge accessible and actionable. Conversely, a supportive culture may be highly important while occupying an effect-side position in the expert-judgment network. This technical label indicates that culture received more perceived influence than it dispatched within the modeled system; it does not establish an empirical causal mechanism. This is why the study reports priority and net directional position as separate outputs.

2.3 Integrating TPB, SECI, and organizational KM capabilities

TPB explains how attitude, subjective norms, and perceived behavioral control shape intention and behavior (Ajzen, 1991). Bock et al. (2005) apply related constructs to knowledge-sharing intention. Because sharing concerns contributor behavior, their findings do not directly test recipient-side acquisition; they support treating attitude, norms, and control as plausible conditions for knowledge seeking and acceptance. TPB therefore supplies the individual behavioral layer, but the expert weights are not employee-level behavioral coefficients.

SECI provides a complementary process layer. Nonaka (1994) explains organizational knowledge creation through interaction between tacit and explicit knowledge. Formal and informal interaction, communication skills, time, and recognition of knowledge

value can enable socialization and externalization; technology and structure can support combination; learning opportunities and practice can support internalization. The present expert data prioritize enablers of these processes but do not observe the conversion processes directly.

An organizational-capabilities perspective connects these layers. Gold *et al.* (2001) identify technology, structure, and culture as KM infrastructure capabilities and acquisition, conversion, application, and protection as process capabilities. Lee and Choi (2003) likewise link collaboration, trust, learning, centralization, formalization, skills, and IT support to knowledge-creation processes. Recent evidence reinforces the interdependence of technical and social resources: digital transformation can reshape collaboration, long-term orientation, and other cultural attributes rather than operating as a purely technical change (Pfaff *et al.*, 2023), while maritime technological and organizational learning resources are associated with innovation and resilience (Li *et al.*, 2024). Rewards are included because empirical and meta-analytic research identifies motivational benefits, costs, reputation, reciprocity, and context as relevant to knowledge contribution (Kankanhalli *et al.*, 2005; Nguyen *et al.*, 2019). A holistic KM maturity framework similarly treats effective KM as an integrated system of critical success factors aligned with ISO 30401 rather than as an isolated technology initiative (Bougoulia & Glykas, 2023).

Readiness evidence from an Iranian military university likewise shows that KM implementation depends on uneven organizational conditions: management was the most influential preparatory dimension, human resources showed the highest readiness, and organizational structure the lowest (Fathi *et al.*, 2020). This evidence supports diagnosing the capability

configuration before selecting a KM intervention rather than assuming that technology alone creates readiness.

The three perspectives are integrated as a nested opportunity–motivation–conversion mechanism rather than as a single causal theory. Organizational capabilities define the opportunity structure: structure allocates authority and time, IT enables access and retrieval, rewards signal value, and culture establishes norms and trust (Gold et al., 2001; Lee & Choi, 2003). Within that context, TPB specifies the motivational gateway through which perceived control, attitudes, and norms orient deliberate knowledge seeking and acceptance (Ajzen, 1991). SECI then provides a conversion lens for how tacit and explicit knowledge are made accessible, articulated, combined, and internalized once engagement occurs (Nonaka, 1994). SECI is used here only to interpret enabling conditions around acquisition; it does not equate acquisition with creation, sharing, or transfer. Feedback from successful or failed acquisition may update attitudes, norms, routines, and capability investments, but these feedback paths are conceptual and are not empirically estimated in this study.

2.4 Hierarchical criterion architecture

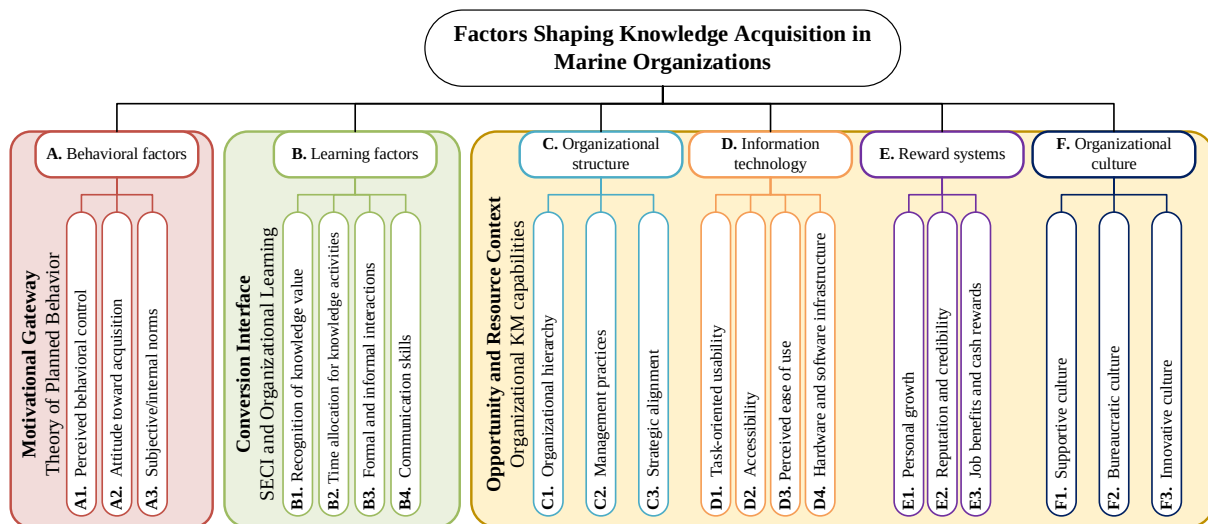
The six clusters operationalize the linked opportunity-motivation-conversion framework. Behavioral factors form the motivational gateway (A), and learning factors capture conversion-enabling conditions (B). Organizational structure, information technology, reward systems, and culture define the opportunity, reinforcement, and normative context (C-F). These layers are analytically distinguishable but not assumed to be independent; for example, technology affects opportunity, rewards can affect motivation, and culture conditions both engagement and conversion. Table 1 maps the six clusters and 20 operational sub-criteria to their theoretical and empirical source base.

B1 is defined as recognition of knowledge value. D1 and D3 are retained as distinct criteria because they represent different properties of technology use. Drawing on the outcome-oriented concept of usability in ISO 9241-11:2018, D1 task-oriented usability denotes the extent to which a technology enables users to complete knowledge-acquisition tasks successfully, including locating, retrieving, and accessing relevant knowledge in the intended operational context (International Organization for Standardization, 2018). Consistent with Davis (1989), D3 perceived ease of use denotes the extent to which learning and operating the technology is straightforward, understandable, and requires minimal mental or operational effort. Thus, D1 concerns successful task accomplishment in context, whereas D3 concerns the effort required to learn and operate the technology.

Figure 1 presents the criterion architecture as three complementary analytic layers. The opportunity and resource context contains the organizational enabling conditions in clusters C–F; TPB anchors the motivational gateway in cluster A; and SECI and organizational-learning research inform the conversion interface in cluster B. The grouping and connector lines indicate classification and membership, not a causal sequence. Cross-layer interdependencies are elicited from expert judgments through DEMATEL and synthesized through DANP rather than imposed a priori. The framework therefore defines the theoretical boundary of each cluster while avoiding untested claims about independent variables, mediation, moderation, feedback, or causal coefficients.

Table 1. Source map for the six clusters and 20 sub-criteria.

Code	Cluster	Sub-criteria	Source basis	Theoretical role
A	Behavioral factors	A1 perceived behavioral control A2 attitude toward acquisition A3 subjective/internal norms	Ajzen (1991); Bock <i>et al.</i> (2005)	Motivational gateway: intention and perceived agency
B	Learning factors	B1 recognition of knowledge value B2 time for knowledge activities B3 formal/informal interaction B4 communication skills	Fei (2011); Lee & Choi (2003); Pauksztat (2021); Sreen <i>et al.</i> (2024); Wang & Noe (2010)	Conversion interface: attention, interaction, communication, and time
C	Organizational structure	C1 hierarchy C2 management practices C3 strategic alignment	Gold <i>et al.</i> (2001); Lee & Choi (2003)	Opportunity structure: authority, coordination, and strategic alignment
D	Information technology	D1 task-oriented usability D2 accessibility D3 perceived ease of use D4 hardware/software infrastructure	Alavi & Leidner (2001); Davis (1989); Fei (2011); Gold <i>et al.</i> (2001); International Organization for Standardization (2018); Liu & Cheng (2024)	Digital opportunity: access, retrieval, combination, and reuse support
E	Reward systems	E1 personal growth E2 reputation/credibility E3 job benefits/cash rewards	Bock <i>et al.</i> (2005); Kankanhalli <i>et al.</i> (2005); Nguyen <i>et al.</i> (2019)	Value signaling: participation incentives and reinforcement
F	Organizational culture	F1 supportive culture F2 bureaucratic culture F3 innovative culture	Gold <i>et al.</i> (2001); Lee & Choi (2003); Pfaff <i>et al.</i> (2023); Wang & Noe (2010)	Normative context: trust, learning climate, and acceptable behavior

**Figure 1.** Opportunity-motivation-conversion architecture for knowledge acquisition in Iranian marine organizations.

3. Method

3.1 Research design

The empirical design is an expert-judgment network-prioritization study. It identifies perceived direct influences and derives system priorities; it does not estimate population parameters or employee-level behavioral relationships. DANP was selected because the research question concerns interdependence and network-adjusted priority among a fixed set of criteria. Independent-weighting methods such as AHP would not represent feedback among criteria, whereas structural-equation, multilevel, and longitudinal designs would answer a different

question by testing measured relationships in larger observational or repeated samples. The opportunity-motivation-conversion framework guides criterion selection and interpretation, but does not impose a prespecified causal path structure on the influence matrix. The method is described as DANP because the total-relation matrix supplies the network supermatrix rather than requiring a second, separate 1-9 ANP pairwise-comparison survey (Gölcük & Baykasoğlu, 2016). This construction has precedent in KM strategy analysis (Wu, 2008) and remains in current use for systems with interdependent criteria (Lin *et al.*, 2025).

3.2 Panel, instrument, and data collection

A purposive panel of 20 experts working in Iran's marine sector was recruited from marine operations, safety management, ship operations, and academic/KM roles. The instrument was piloted with five domain experts who were not members of the final panel, and its content was reviewed by three senior researchers. The direct-influence questionnaire used a common 0-4 scale (0 = no influence, 1 = low, 2 = moderate, 3 = high, 4 = very high) for the perceived influence of criterion *i* on criterion *j*; diagonal judgments were fixed at zero. Within the technology cluster, D1 captured successful accomplishment of knowledge-acquisition tasks, whereas D3 captured simplicity of learning and operation and the effort required from users. The analytical dataset contains the 20 completed individual 20 x 20 direct-influence matrices. It does not contain a separate set of reciprocal 1-9 ANP pairwise-comparison matrices. The panel was designed for cross-functional expert elicitation rather than statistical representation; accordingly, 20 is treated as the size of a bounded judgment panel, not as an empirical sample size that supports population inference. Coverage across roles was used to broaden the professional viewpoints represented, but it cannot eliminate recruitment-network or shared-sector bias.

All final-panel members completed the same direct-influence instrument and received equal analytical weight. A separate matrix was retained for every expert, and aggregation occurred only at the analytical stage; no response was weighted by job title, employer, or seniority. This preserves respondent-level variation for agreement, LOEO, and aggregation-sensitivity checks, but it does not guarantee sociological independence because shared training, professional networks, or sector experience may still produce common assumptions. The primary group direct-relation matrix *Z* was

therefore formed by the cellwise arithmetic mean, which represents the centroid of equally weighted judgments on the shared bounded 0-4 scale. Geometric aggregation was not used because the entries were additive influence ratings rather than reciprocal ratio-scale comparisons. Recognizing that the categories are ordered and that the arithmetic mean can be influenced by extreme ratings, we also reran the complete DEMATEL-DANP chain using the cellwise median and a 10% symmetric trimmed mean; with 20 experts, the latter removed the two lowest and two highest ratings in each off-diagonal cell. The individual matrices were retained for agreement, LOEO, and aggregation-sensitivity analyses.

All 20 experts were drawn from organizations operating in Iran's marine sector. Table 2 summarizes the panel by age, marine-sector experience, academic qualification, primary specialization, organization type, and gender. The experts had a mean age of 46.2 years (SD = 5.3) and an average of 15.7 years of marine-sector experience (SD = 4.6). Master's degrees were most common (45%), followed by doctorates (30%) and bachelor's degrees (25%). Marine operations (35%) and ship or technical operations (30%) formed the largest specialization groups. Half of the experts worked for shipping companies or vessel operators, and the panel comprised 18 men (90%) and two women (10%). The profile combines operational, safety, technical, and academic/KM perspectives, while the purposive composition does not imply statistical representativeness of Iran's wider marine workforce.

Table 2. *Characteristics of the expert panel.*

Characteristic	Category or statistic	Value	%
Age (years)	Mean (SD)	46.2 (5.3)	—
Experience (years)	Mean (SD)	15.7 (4.6)	—
Education	Doctorate	6	30.0
	Master's degree	9	45.0
	Bachelor's degree	5	25.0

Primary specialization	Marine operations	7	35.0
	Maritime safety and risk management	3	15.0
	Ship or technical operations	6	30.0
	Knowledge management or organizational research	4	20.0
Organization type	Shipping company or vessel operator	10	50.0
	Port, maritime service, or technical organization	4	20.0
	Regulatory, classification, or training organization	2	10.0
	University or research institution	4	20.0
Gender	Male	18	90.0
	Female	2	10.0

3.3 DEMATEL analysis

Let $E^k = [e_{ij}^k]$ denote the direct-influence matrix supplied by expert k . The group matrix is $Z = \frac{1}{20} \sum_{k=1}^{20} E^k$. Its maximum row sum is 49.5 and its maximum column sum is 47.4. Accordingly,

$$\max\{\max_i \sum_j z_{ij}, \max_j \sum_i z_{ij}\} = 49.5 \text{ and } X = \frac{Z}{s}.$$

The total-relation matrix is $T = X(I - X)^{-1}$. For each sub-criterion i , $D_i = \sum_j t_{ij}$ is dispatched influence and $R_i = \sum_j t_{ji}$ is received influence. Prominence is $D_i + R_i$ and net relation is $D_i - R_i$. A positive net relation denotes a cause-side factor and a negative value an effect-side factor. The primary classification uses sums across all 20 criteria. Within-cluster sums are reported only as a diagnostic comparison and are not labeled as full-system values.

Following standard DEMATEL terminology, a positive net relation is labeled cause-side and a negative value effect-side (Gölcük & Baykasoğlu, 2016; Igodo et al., 2023). In this study, these terms indicate the relative directional position of a criterion within the aggregated expert-judgment network; they do not demonstrate real-world causation, predictive effects, or employee-level behavioral relationships.

For clusters p and q , the cluster relation $\bar{t}_q$ is the mean of the corresponding block T^{pq} . Cluster D , R , prominence, and net relation are calculated from the 6×6 block-mean matrix.

The cause-effect maps use $D+R$ on the horizontal axis and $D-R$ on the vertical axis. Positive and negative $D-R$ identify cause-side and effect-side positions, respectively (Igodo et al., 2023), and four-quadrant influential-relation maps distinguish relatively prominent and non-prominent positions (Shooshtarian et al., 2024). These labels refer only to the direction of perceived influence in the modeled expert network. A uniform four-region convention is used in Figures 2 and 3: $D-R = 0$ separates cause-side from effect-side positions, while the mean $D+R$ of the factors displayed in each map is the disclosed operational boundary between relatively high and low prominence. The mean cutoff is map-specific and is not presented as a universal DEMATEL threshold.

3.4 DANP priority synthesis

The total-relation matrix T is partitioned by the six clusters. Within each source–target block T^{pq} , each source row is normalized over the criteria in target cluster q . Transposing the block-normalized matrix yields the unweighted supermatrix W . The cluster relation matrix is row-normalized to T^{Dq} ; each block of W is then multiplied by its corresponding normalized source-to-target cluster influence to obtain the column-stochastic weighted supermatrix W^α (Gölcük & Baykasoğlu, 2016; Lin et al., 2025).

The limit supermatrix is obtained as $\lim_{k \rightarrow \infty} (W^\alpha)^k$. The stable column gives the global sub-criterion priorities, and cluster priorities are obtained by summing the priorities of their member criteria. This cluster-weighted DANP construction is consistent with established ANP and DANP procedures (Gölcük & Baykasoğlu, 2016; Mu et al., 2020).

3.5 Robustness evaluation

Agreement was assessed directly from the 20 observed matrices. For the 380 off-diagonal cells, cell-level dispersion was summarized by the sample standard

deviation. Each expert's mean absolute deviation (MAD) from Z and the mean pairwise absolute difference among the 190 expert pairs were calculated on the original 0–4 scale; normalized agreement indices were obtained as $1 - \text{MAD}/4$. Kendall's coefficient of concordance was calculated from each expert's ranking of the 20 outgoing row sums and, separately, the 20 incoming column sums (Franceschini & Maisano, 2021). These statistics describe different aspects of agreement and are therefore reported together rather than collapsed into a single universal reliability coefficient. The two W values are interpreted descriptively; because no formal test of their difference was specified, their numerical gap is not treated as statistically significant.

Robustness was evaluated through 20 LOEO recalculations. In run k, the aggregate matrix was recomputed from the remaining 19 observed matrices, and the complete DEMATEL-DANP chain was repeated, including normalization, total-relation construction, cluster weighting, supermatrix convergence, priorities, and full-system D-R values. For each criterion and cluster, the minimum and maximum priority, maximum absolute deviation from the full-panel weight, rank retention, and stability of the net-relation sign were recorded. LOEO therefore evaluates internal stability to panel composition; it does not establish external validity, predictive accuracy, or empirical causal validity.

Aggregation-rule sensitivity was evaluated separately from LOEO sensitivity. For the median and 10% trimmed-mean matrices, all normalization, total-relation, cluster-weighting, supermatrix, and convergence steps were recomputed. Robustness was summarized by Spearman rank correlation with the arithmetic-mean solution, the maximum absolute rank shift, and stability of the D–R sign at criterion and cluster levels. The arithmetic-mean solution remained the

primary analysis; alternative aggregators were used only to identify conclusions that depended on the aggregation rule. The network was treated as analytically interpretable only when the weighted supermatrix converged, the reported summaries remained traceable to the observed matrices, and the broad priority pattern and cluster directions were not determined by one expert or one aggregation rule. These are internal coherence and sensitivity criteria; they are not thresholds for empirical truth, prediction, or causal validity.

4. Results

4.1 DEMATEL results

Table 3 reports full-system D and R values and compares each directional class with the within-cluster diagnostic class. Five labels differ by scope: A3 and C3 shift from within-cluster effect-side to full-system cause-side; D1 shifts from within-cluster cause-side to full-system effect-side; and E2 and F3 shift from within-cluster cause-side to full-system effect-side. The distinction is important because within-cluster row and column sums represent a local block rather than the complete perceived-influence system. The LOEO range shows that every full-system net-relation sign is retained across all 20 omissions. The aggregate direct-relation matrix, normalized direct-relation matrix, and total-relation matrix are provided in Appendix A.

Within the aggregated expert-judgment network, the cause-side factors are A1 perceived behavioral control, A2 attitude, A3 subjective/internal norms, B1 recognition of knowledge value, B3 formal/informal interaction, C1 hierarchy, C2 management practices, C3 strategic alignment, D4 hardware/software infrastructure, and E1 personal growth. The effect-side factors are B2 time for knowledge activities, B4 communication skills, D1 usability, D2 accessibility, D3 ease of use, E2

reputation/credibility, E3 job benefits/cash rewards, and all three culture criteria. All net-relation signs remain stable when any one expert is omitted; aggregation-rule sensitivity is reported separately in Section 4.4. Nevertheless, B4, D1, E1, E2, and E3 remain close to the $D-R = 0$ boundary and should be interpreted as weak directional positions rather than strong effects.

Table 3. Full-scope and within-cluster DEMATEL classification

Code	Sub-criterion	D	R	D+R	D-R	Within → global	LOEO min D-R	LOEO max D-R
A1	Perceived behavioral control	5.606	5.044	10.650	0.562	Cause → Cause	0.523	0.631
A2	Attitude toward acquisition	5.818	5.275	11.093	0.542	Cause → Cause	0.505	0.592
A3	Subjective/internal norms	5.461	5.201	10.661	0.260	Effect → Cause	0.180	0.308
B1	Recognition of knowledge value	5.043	4.556	9.600	0.487	Cause → Cause	0.436	0.535
B2	Time for knowledge activities	5.019	5.226	10.246	-0.207	Effect → Effect	-0.293	-0.162
B3	Formal/informal interaction	5.253	5.069	10.322	0.184	Cause → Cause	0.128	0.214
B4	Communication skills	4.219	4.276	8.495	-0.057	Effect → Effect	-0.116	-0.012
C1	Hierarchy	3.662	3.345	7.006	0.317	Cause → Cause	0.268	0.383
C2	Management practices	5.405	4.987	10.391	0.418	Cause → Cause	0.368	0.459
C3	Strategic alignment	5.310	4.967	10.277	0.343	Effect → Cause	0.297	0.380
D1	Task-oriented usability	4.521	4.587	9.108	-0.066	Cause → Effect	-0.117	-0.006
D2	Accessibility	4.550	5.126	9.676	-0.576	Effect → Effect	-0.620	-0.504
D3	Perceived ease of use	4.506	4.951	9.457	-0.446	Effect → Effect	-0.492	-0.410
D4	Hardware/software infrastructure	5.081	4.629	9.710	0.452	Cause → Cause	0.384	0.510
E1	Personal growth	4.666	4.625	9.291	0.040	Cause → Cause	0.010	0.093
E2	Reputation/credibility	4.560	4.623	9.183	-0.063	Cause → Effect	-0.098	-0.006
E3	Job benefits/cash rewards	4.046	4.152	8.198	-0.105	Effect → Effect	-0.154	-0.058
F1	Supportive culture	4.498	5.583	10.081	-1.084	Effect → Effect	-1.165	-1.041
F2	Bureaucratic culture	4.239	4.909	9.147	-0.670	Effect → Effect	-0.719	-0.627
F3	Innovative culture	4.341	4.671	9.012	-0.329	Cause → Effect	-0.360	-0.272

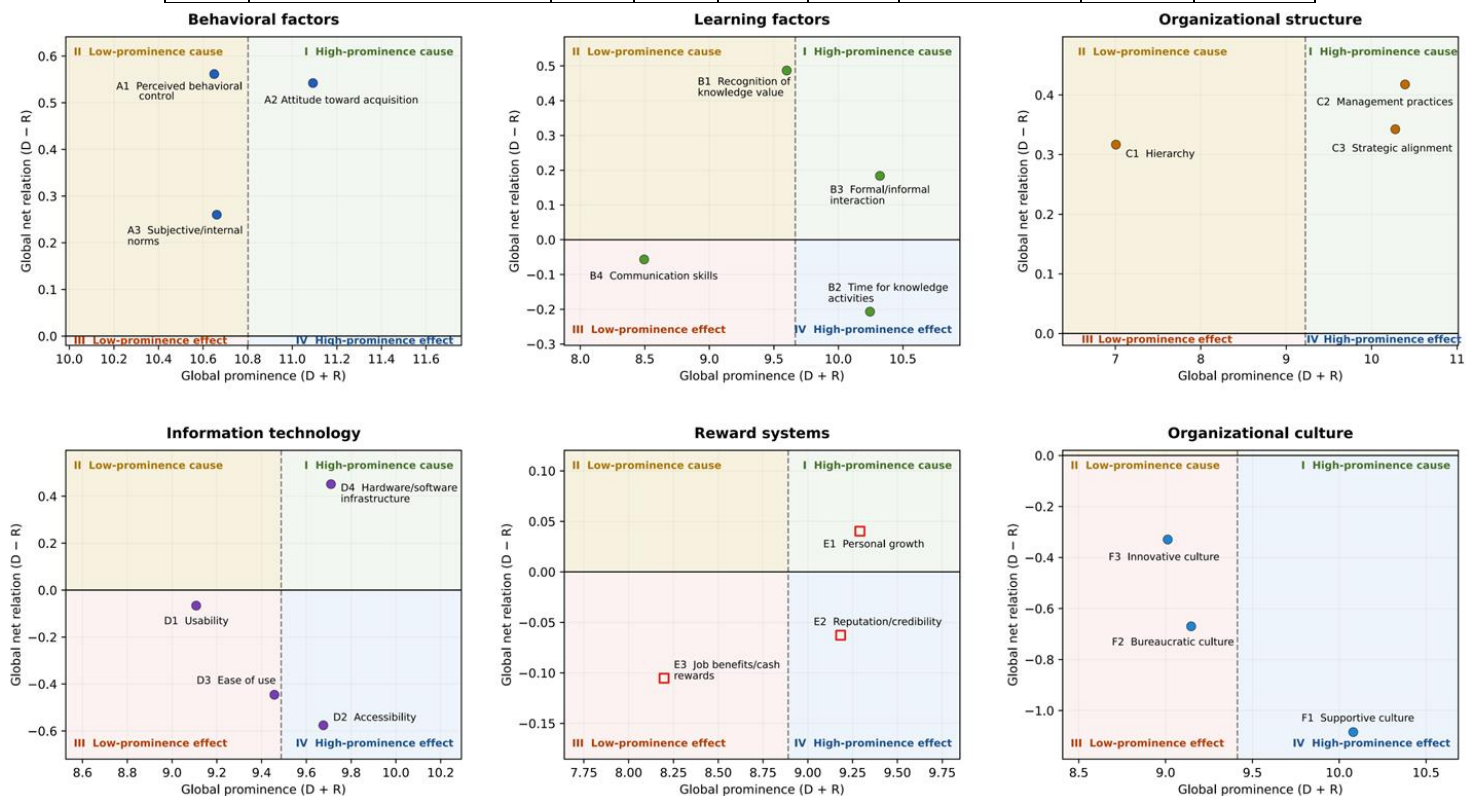


Figure 2. Full-system DEMATEL maps by cluster.

Note: The vertical dashed line in each panel is the cluster-specific mean prominence, and the horizontal line is $D-R = 0$.

Table 4. Cluster-averaged total-relation matrix and DEMATEL summaries.

Cluster	A	B	C	D	E	F	D	R	D+R	D-R	Class
A	0.298	0.274	0.262	0.289	0.267	0.300	1.689	1.554	3.243	0.134	Cause
B	0.256	0.246	0.232	0.248	0.226	0.256	1.463	1.434	2.897	0.029	Cause
C	0.256	0.247	0.208	0.243	0.223	0.256	1.434	1.328	2.762	0.106	Cause
D	0.255	0.234	0.216	0.225	0.221	0.251	1.402	1.450	2.852	-0.048	Effect
E	0.248	0.216	0.203	0.227	0.200	0.232	1.327	1.340	2.667	-0.013	Effect
F	0.242	0.218	0.207	0.218	0.203	0.220	1.308	1.516	2.823	-0.208	Effect

4.2 Cluster-level influence structure

Table 4 aggregates the total-relation matrix into six source–target cluster blocks and reports the associated D , R , prominence, and net-relation summaries.

As shown in Table 4, behavioral factors ($D-R = 0.134$) and organizational structure (0.106) occupy the clearest cause-side positions in the perceived-influence network. Learning is only slightly positive (0.029). Information technology (-0.048) and rewards (-0.013) are close to zero, while organizational culture is more clearly effect-side (-0.208). Learning, IT, and rewards should therefore be interpreted cautiously rather than as unambiguous upstream intervention levers.

Figure 3 places the six clusters on the prominence–net-relation plane using the same four-region convention as Figure 2. $D-R = 0$ separates cause-side from effect-side clusters, and the mean cluster prominence ($D+R = 2.874$) separates relatively high from relatively low prominence within this map. Behavioral factors and learning occupy the high-prominence cause region; organizational structure is a low-prominence cause. Information technology, rewards, and organizational culture occupy the low-prominence effect region. The small absolute net relations for learning, IT, and rewards warrant cautious interpretation even though their signs are stable in the LOEO analysis.

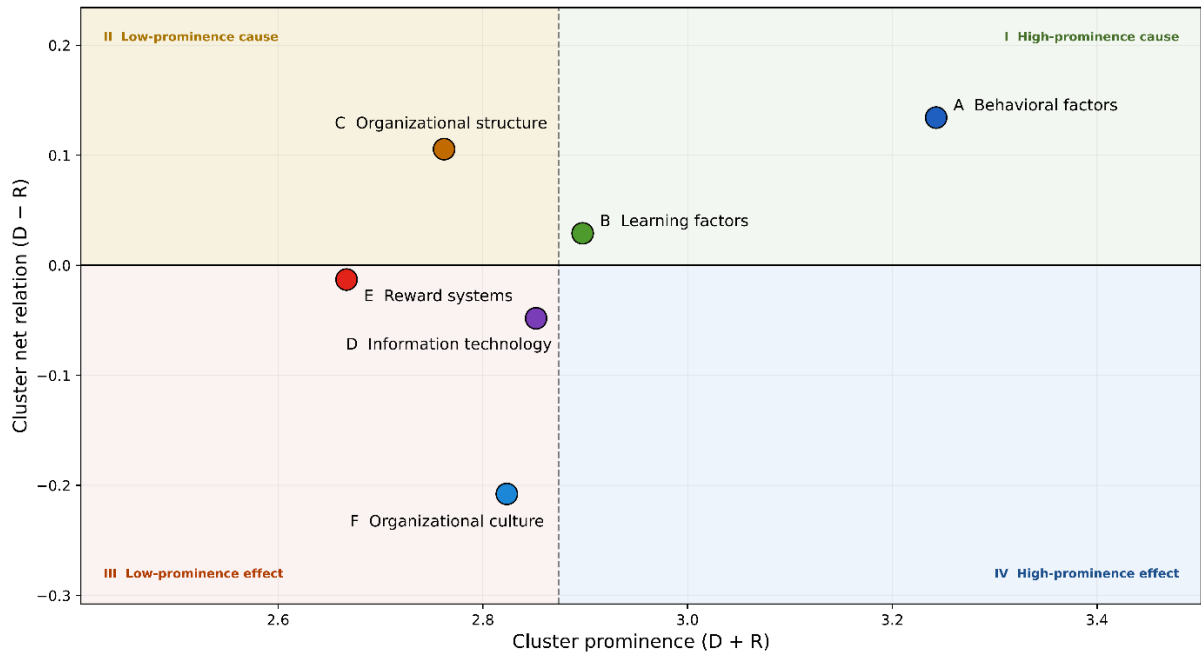


Figure 3. Cluster-level DEMATEL map based on the block-mean total-relation matrix.

4.3 DANP priorities

Table 5 reports the priorities of the six clusters, while Table 6 provides the complete

global ranking of the 20 sub-criteria derived from the limit supermatrix. The sub-criterion weights represent relative network priorities

within the expert-derived system and should not be interpreted as effect sizes, probabilities, performance scores, or estimates of intervention gains. Higher-ranked criteria may warrant earlier diagnostic and pilot attention; however, implementation sequencing should also account for directional position, feasibility, and organizational context. Reporting cluster and sub-criterion priorities separately prevents cluster totals from being confused with sub-criterion weights.

Tables 5 and 6 show that behavioral factors rank first (0.1805), but organizational culture (0.1756), IT (0.1680), and learning (0.1663)

are close. The ordering should therefore be read as a portfolio of mutually dependent conditions, not as a claim that one cluster dominates the system. In Table 6, supportive culture ranks first among sub-criteria (0.0645) but is a robust effect-side factor; attitude (0.0614), subjective/internal norms (0.0603), and perceived behavioral control (0.0587) combine high priority with robust cause-side roles. Management practices (0.0578) and strategic alignment (0.0577) also combine relatively high priority with robust positive D–R.

Table 5. Cluster priorities from the cluster-weighted limit supermatrix.

Code	Cluster	DANP weight	DEMATEL class	D–R	Rank
A	Behavioral factors	0.1805	Cause	0.134	1
F	Organizational culture	0.1756	Effect	-0.208	2
D	Information technology	0.1680	Effect	-0.048	3
B	Learning factors	0.1663	Cause	0.029	4
E	Reward systems	0.1554	Effect	-0.013	5
C	Organizational structure	0.1542	Cause	0.106	6

Table 6. Global sub-criterion priorities from the limit supermatrix.

Code	Sub-criterion	Cluster	Global weight	Rank
F1	Supportive culture	F	0.0645	1
A2	Attitude toward acquisition	A	0.0614	2
A3	Subjective/internal norms	A	0.0603	3
A1	Perceived behavioral control	A	0.0587	4
C2	Management practices	C	0.0578	5
C3	Strategic alignment	C	0.0577	6
F2	Bureaucratic culture	F	0.0569	7
F3	Innovative culture	F	0.0541	8
E1	Personal growth	E	0.0536	9
E2	Reputation/credibility	E	0.0536	10
E3	Job benefits/cash rewards	E	0.0481	11
B2	Time for knowledge activities	B	0.0453	12
D2	Accessibility	D	0.0447	13
B3	Formal/informal interaction	B	0.0440	14
D3	Perceived ease of use	D	0.0431	15
D4	Hardware/software infrastructure	D	0.0403	16
D1	Task-oriented usability	D	0.0400	17
B1	Recognition of knowledge value	B	0.0397	18
C1	Organizational hierarchy	C	0.0388	19
B4	Communication skills	B	0.0373	20

Within rewards, personal growth (0.053618) and reputation/credibility (0.053608) are effectively tied, while job benefits/cash rewards have weight 0.048137. The full-panel difference between personal growth and reputation is only 0.000011, and their ordering reverses in some LOEO runs. Reputation exceeds cash rewards by

0.005471. The point estimates place E1 and E2 above E3 in the full-panel solution, but this numerical ordering should not be interpreted as practical or universal superiority of non-financial rewards. The close weights and panel-based design support a differentiated reward portfolio rather than a definitive hierarchy.

4.4 Observed agreement and robustness

Table 7 summarizes cluster-priority robustness across the 20 LOEO recalculations, including the minimum and maximum priority, maximum absolute change from the full-panel result, and baseline-rank retention. The narrow ranges and high rank-retention rates indicate limited sensitivity of the broad cluster-priority pattern

Table 7. Cluster-priority robustness under LOEO analysis.

Cluster	Baseline	LOEO minimum	LOEO maximum	Maximum $ \Delta \text{weight} $	Rank retention
Behavioral factors	0.1805	0.1794	0.1813	0.0011	100.0%
Learning factors	0.1663	0.1657	0.1671	0.0008	100.0%
Organizational structure	0.1542	0.1532	0.1551	0.0011	95.0%
Information technology	0.1680	0.1673	0.1685	0.0007	100.0%
Reward systems	0.1554	0.1548	0.1559	0.0005	95.0%
Organizational culture	0.1756	0.1751	0.1762	0.0006	100.0%

The largest absolute cluster-weight change is 0.001074 and the largest sub-criterion change is 0.000944. Behavioral factors retain rank 1, organizational culture rank 2, information technology rank 3, and learning rank 4 in every omission. Structure and rewards exchange their adjacent fifth and sixth positions in one of the 20 runs, giving 95% rank retention for each. Supportive culture remains the highest-priority sub-criterion in all runs. These results indicate that the main priority pattern is not driven by a single expert. Operationally, the stable upper tier can guide where diagnosis and pilot design begin, whereas the adjacent structure-reward order should not be used to justify materially different resource commitments.

The reward results require finer interpretation. Across omissions, the personal-growth minus reputation/credibility difference ranges from -0.000516 to 0.000430 ; personal growth ranks above reputation in 55% of the runs. Their practical ordering is therefore unresolved. By contrast, both remain above job benefits/cash rewards in every omission. This stability supports the ordering within the observed panel, not substantive superiority or transfer to other organizations. Across LOEO runs, E1 remains weakly cause-side and E2 and E3

to the omission of any single expert. It does not demonstrate predictive accuracy, external validity, or implementation success. Decision-makers can therefore use stable priority tiers to organize diagnosis and pilots, while avoiding rigid budget or implementation sequences based on small differences between adjacent ranks.

remain weakly effect-side. Median aggregation, however, reverses E1 and E2, whereas the 10% trimmed mean preserves their arithmetic-mean signs. Their small D–R magnitudes therefore warrant caution.

Observed agreement is moderate to high but not uniform across dimensions. The mean cell standard deviation is 0.753 on the 0–4 scale. Mean expert MAD from the aggregate is 0.479, corresponding to a normalized MAD agreement index of 0.880. The mean pairwise absolute difference is 0.665 and the corresponding pairwise agreement index is 0.834. Kendall's W is 0.710 for outgoing-influence rankings and 0.554 for incoming-influence rankings. Both coefficients indicate nontrivial concordance, but the larger outgoing W shows that experts' rankings are more aligned for criteria as sources of influence than for criteria as recipients. The numerical gap is interpreted descriptively and is not evidence of a statistically significant difference between the two concordance coefficients.

Aggregation sensitivity supported the stability of the main priority pattern. Relative to the arithmetic-mean solution, sub-criterion ranks correlated at $\rho = 0.989$ for the median and $\rho = 0.994$ for the 10% trimmed mean, with a maximum shift of two ranks. Cluster-

rank correlations were $\rho = 0.943$ and 1.000 , respectively; behavioral factors, organizational culture, information technology, and learning retained positions 1–4, while structure and rewards exchanged adjacent positions 5 and 6 under the median. All six cluster D–R signs were preserved. At the sub-criterion level, the trimmed mean preserved every D–R sign, whereas the median reversed D1, E1, and E2. Their arithmetic-mean D–R values were close to zero (-0.066 , 0.040 , and -0.063), so these three direction labels are treated as aggregation-sensitive rather than robust. The arithmetic-mean priorities and rankings reported in Tables 5 and 6 are unchanged.

5. Discussion

5.1 Interpreting priority and directional position together

The cluster-weighted DANP results place behavioral factors first, closely followed by culture, information technology, and learning. DANP priority indicates systemic importance within the weighted expert network; DEMATEL D–R indicates the balance of dispatched and received perceived influence. The measures are complementary, not interchangeable. A high-priority effect-side condition warrants attention, but it does not by itself identify an effective intervention.

Supportive culture illustrates the distinction. Its first-ranked weight shows systemic importance, whereas negative D–R means experts judged it to receive more influence than it dispatched. The result neither marginalizes culture nor proves direct culture programs ineffective; it supports testing them with aligned management practices, norms, time, interaction routines, and infrastructure. Veltsin et al. (2025) report a similar perceived pattern in maritime safety: training, leadership, and communication were cause-side, while safety culture was effect-side. In both expert networks, culture appears

more emergent than an isolated upstream lever, but neither study establishes causation.

The behavioral cluster combines the highest priority with robust cause-side positions for perceived control, attitude, and norms. This pattern is consistent with TPB's separation of feasibility, evaluation, and social expectation, but it is not a test of TPB coefficients or employee behavior. It supports piloting a sequence that first makes acquisition feasible, socially expected, and worthwhile, followed by empirical evaluation of whether behavior changes.

Learning criteria are directionally mixed. Knowledge-value recognition and formal/informal interaction are cause-side; time and communication skills are effect-side. All four signs survive LOEO, although communication skills has a weak net position. Fei (2011), Mallam et al. (2022), and Pauksztat (2021) help explain the split: personnel may value and seek knowledge, while available time and workable communication channels depend on staffing, work design, language, and management systems. Value recognition is therefore a motivational entry point, whereas time and communication are context-dependent enablers.

The outgoing-incoming concordance asymmetry reinforces this caution. Experts agreed more on which criteria dispatch influence than on which criteria receive it. Sources such as management practices, infrastructure, incentives, and norms are visible across roles, whereas recipient-side dependence varies by ship or shore position and operational, technical, or knowledge-management responsibilities. The result supports using the broad source-side ordering for initial diagnosis while treating incoming patterns and near-zero D–R values as context-sensitive. This remains an interpretation; the difference between the two W values was not formally tested.

5.2 Theoretical contribution

The first theoretical contribution is a linked opportunity–motivation–conversion account rather than a simple juxtaposition of three theoretical perspectives. Organizational capabilities determine whether relevant knowledge is accessible, legitimate, and organizationally supported (Gold et al., 2001; Lee & Choi, 2003); TPB explains whether actors intend and feel able to seek or accept that knowledge (Ajzen, 1991); and SECI explains how interaction and representation can convert accessible tacit and explicit knowledge into forms that recipients can interpret and internalize (Nonaka, 1994). The layers are connected by conceptual feedback: successful acquisition can reinforce attitudes and norms and reveal capability gaps, while culture, incentives, structure, and infrastructure condition subsequent engagement. DANP maps expert-perceived interdependencies among these conditions; it does not estimate this conceptual sequence as a causal path model.

The second contribution is the distinction between theoretical relevance, network priority, and net directional position. A theoretically central condition need not receive the highest network weight, and a highly weighted condition need not occupy an upstream position. Supportive culture illustrates this point: it is first in the DANP ranking but strongly effect-side in the DEMATEL map. This distinction extends a simple list of KM enablers by showing how importance and perceived directional position can diverge in an interdependent marine knowledge-acquisition system.

The third contribution concerns the level at which interdependence is interpreted. Full-system D and R sums describe perceived influence across the complete 20-criterion network, whereas within-cluster sums describe only a local subsystem. Five directional classifications change when the full network is used. Because all full-system

net-relation signs remain unchanged in the 20 LOEO runs, the scope differences are internally stable to omission of any one respondent. Aggregation-rule sensitivity adds an important qualification: cluster signs and the main priority ordering are stable, but the near-zero criterion-level directions of D1, E1, and E2 depend on use of the median rather than the arithmetic or trimmed mean. These stability results do not constitute external or causal validation.

5.3 Managerial and policy implications

The combined priority and directional-position results support an operations-aligned stage-gate sequence rather than a single ranked intervention or a fixed calendar. Governance should be proportionate to organizational scale. Large multi-vessel operators may convene a ship-shore steering group, whereas small and medium-sized operators should assign the same functions to an existing operations, safety, or quality manager, supported where feasible by a knowledge champion, without creating a new committee. Before a selected voyage, crew-rotation, contract, or dry-dock cycle, this accountable lead should assign ownership for each knowledge domain and diagnose whether acquisition fails because personnel cannot locate relevant knowledge, do not regard it as valuable, lack time or authority to obtain it, or cannot interpret it within an operational decision. Baselines should cover retrieval time, unsuccessful searches, unresolved handover issues, participation in debriefs, reuse of documented lessons, and closure of safety or operational learning actions.

At the pilot gate, timed to a voyage or crew rotation, managers should test behavioral and learning interventions on selected vessels and shore units. They can strengthen perceived control through clear access authority, simpler approval routes, connectivity, tools, and protected time. Masters and line

managers should reinforce norms through mentoring and visible use of prior lessons; reviews and debriefs should link acquired knowledge to safety and work quality. Sreen et al. (2024) distinguish interactive controls that support acquisition from failure from diagnostic controls that may inhibit it, supporting participative rather than compliance-only debriefs. Nguyen et al. (2024) examine sharing, not acquisition, but show why leadership may be insufficient without an innovative organizational setting.

The pilot should also protect structured opportunities for interaction. Fleet and human-resource managers can embed handover protocols, simulation-based training, cross-functional reviews, and ship-shore communities of practice in duty schedules, while multilingual facilitation can reduce communication barriers (Pauksztat, 2021). These mechanisms should be part of normal operations rather than discretionary additions, because time for knowledge work is an effect-side condition that depends on staffing, schedules, and managerial priorities. Participation, lesson quality, reuse, and overdue follow-up actions should be reviewed at natural operational checkpoints, such as voyage completion, handover, crew change, or incident review, rather than against a uniform monthly deadline.

Scaling should follow evidence and feasibility gates aligned with dry-dock, maintenance, contract, budget, and crew windows. Management should remove hierarchical bottlenecks and align acquisition with safety strategy; information-technology owners should correct diagnosed access failures through connectivity, search, access rights, usable interfaces, and maintainable infrastructure. Resource-constrained operators can start with one vessel or recurring process and reuse existing systems. The cited studies address different links: Fei (2011) finds that information technology supports transfer with culture and leadership;

Pfaff et al. (2023) show that digital transformation can reshape culture; Liu and Cheng (2024) demonstrate a searchable accident knowledge graph. Together they reject a technology-only response, but do not validate the DANP priorities. Scale decisions should therefore test retrieval, interpretation, and reuse rather than repository volume.

Related hybrid decision-support research allocates KM tools and practices to specific organizational knowledge problems under explicit criteria and constraints (Yavari et al., 2024). The present DANP model does not solve an allocation problem. Its weights should therefore guide diagnosis and pilot design, not be converted directly into budget shares, technology purchases, or claims of implementation effectiveness.

Reward and cultural policies should be reviewed at the same operational checkpoints rather than on a uniform quarterly schedule. Personal development, recognition, reputation, and financial benefits may be combined, but the near tie between personal growth and reputation and the small reputation-cash difference do not justify a universal reward hierarchy. Because anticipated extrinsic rewards can have unintended effects on knowledge-sharing attitudes (Bock et al., 2005), management should monitor perceived fairness, contribution quality, knowledge reuse, and the motivational consequences of the reward mix and should adapt that mix by role and operating context. Supportive culture is best treated as a system-level outcome of coherent behavior, work design, structure, technology, and leadership rather than as an isolated campaign.

At the policy level, maritime authorities and industry bodies can promote interoperable incident vocabularies, common learning-report formats, and safeguards for transferring lessons across organizational boundaries without compromising confidentiality. The accountable governance lead should compare

baseline and post-cycle values for retrieval time, lesson reuse, action closure, recurrent handover problems, and relevant operational and safety outcomes at predefined gates aligned with voyage completion, crew rotation, contract renewal, or dry-dock and maintenance windows, then decide whether each pilot should stop, be adapted, or scale. The duration of each stage may therefore differ by vessel type, route, crewing model, contract structure, and available resources. Subsequent comparisons across vessel types and regulatory settings can establish where this expert-derived sequence transfers and where it requires modification.

The Iranian context adds important boundary conditions to implementation. Evidence from southern Iranian ports identifies customs-related issues and poor goods-flow management as major delay factors (Karimi et al., 2025), and sanctions have affected efficiency across major Iranian container ports (Zarbi et al., 2019). Recent stakeholder evidence also characterizes Iran's maritime sector as operating under sanctions and infrastructure constraints while identifying digital infrastructure as an investment priority (Kabiri et al., 2026). Government-facing administrative coordination across port, customs, and related agencies may therefore make management practices, access authority, and strategic alignment especially salient, while technology-access constraints may slow procurement, integration, and maintenance of IT solutions. These are contextual propositions rather than explanations of the DANP estimates: neither administrative structure nor sanctions and technology access was modeled as a separate criterion, so no weight or D-R position can be attributed to them. Organizations should test these boundary conditions locally before scaling, and future research should model them explicitly or compare ports with different regulatory and technology-access profiles.

5.4 Limitations and future research

The 20 experts were purposively selected from Iran's marine sector, so the results are not population estimates for either the wider Iranian marine workforce or marine organizations in other national settings. As Table 2 shows, the panel was predominantly male (90%) and half of its members were affiliated with shipping companies or vessel operators; transferability to differently composed workforces, vessel types, organizational settings, and regulatory regimes should therefore be assessed cautiously. The observed individual matrices permit direct agreement, LOEO, and aggregation-sensitivity analysis, but the panel remains small and judgment-based. Agreement statistics do not eliminate the possibility of shared professional assumptions, and arithmetic aggregation gives every expert equal influence by design. The lower incoming-influence *W* also indicates greater panel dispersion in recipient-side rankings; these pathways may be especially sensitive to expert role and operating setting and should be replicated by subgroup, vessel or shore context, and site. Although priority rankings were highly correlated across the three aggregation rules and all cluster signs were preserved, median aggregation reversed the near-zero D-R signs of D1, E1, and E2. Future studies should compare alternative expert-weighting rules and panels drawn from multiple countries and organizational contexts.

The results represent structured expert judgments rather than employee-level behavioral effects or empirically verified causal relationships. The opportunity-motivation-conversion mechanism organizes criterion selection and interpretation; its feedback paths are not tested as latent, mediation, or longitudinal relationships. D1 task-oriented usability and D3 perceived ease of use were retained as distinct operational

criteria: D1 concerns successful completion of knowledge-acquisition tasks, whereas D3 concerns simplicity and the mental or operational effort required. Their different network positions are consistent with, but do not independently prove, this conceptual distinction. Future studies should preserve these explicit definitions during instrument development and pilot testing, retain individual unrounded judgments, pre-register aggregation and robustness procedures, and use survey, longitudinal, or intervention designs when the objective is to test behavioral relationships, knowledge-conversion processes, operational outcomes, or changes over time.

6. Conclusion

This study provides a theory-informed expert network analysis of knowledge acquisition in Iran's marine sector using 20 observed individual judgment matrices. DANP places behavioral factors first but shows close priorities across culture, IT, and learning. Full-system DEMATEL places behavioral conditions, recognition of knowledge value, organizational hierarchy and management practices, strategic alignment, hardware/software infrastructure, and personal growth on the cause side of the perceived-influence network. Culture is systemically important but predominantly effect-side, while the reward point estimates are close and do not establish a universal preference for non-financial over monetary rewards. The observed judgments show stronger concordance for outgoing than incoming influence rankings, suggesting greater context sensitivity in the recipient-side structure; the numerical difference between the two W values was not formally tested. All full-system net-relation signs remain stable when any one expert is omitted. Priority rankings also remain highly concordant under median and 10% trimmed-mean aggregation, although the median

reverses three near-zero sub-criterion direction labels. These findings support an integrated managerial portfolio rather than a single-factor prescription and demonstrate the value of reporting theoretical relevance, network priority, directional position, agreement, and internal robustness as distinct forms of evidence.

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Appendix A. Detailed analytical matrices

Table A1. Aggregate direct-relation matrix *Z*

	A1	A2	A3	B1	B2	B3	B4	C1	C2	C3	D1	D2	D3	D4	E1	E2	E3	F1	F2	F3
A1	0.0	3.4	3.4	0.0	2.6	2.8	1.5	1.3	3.1	2.8	2.3	3.5	2.1	2.6	2.1	3.1	3.0	3.1	2.8	2.3
A2	3.5	0.0	3.4	2.3	3.0	2.9	1.4	1.3	3.3	2.3	2.4	3.5	2.4	2.8	2.0	2.5	2.5	3.3	2.3	2.4
A3	3.1	3.1	0.0	2.1	2.9	2.4	1.1	1.0	3.3	2.1	2.3	3.5	2.3	2.5	1.9	2.6	2.4	3.3	2.1	2.3
B1	1.8	1.9	2.4	0.0	3.4	3.1	2.8	2.0	2.9	2.1	2.0	2.0	2.5	2.4	1.8	1.4	1.5	2.9	2.1	2.0
B2	1.8	2.3	2.8	2.8	0.0	2.6	2.8	1.9	2.8	2.0	2.1	2.0	2.5	2.4	2.1	1.8	1.1	2.8	2.0	2.1
B3	2.0	2.1	2.9	2.3	3.6	0.0	2.6	2.4	2.6	1.9	2.0	2.5	2.6	2.5	2.5	2.1	1.9	2.6	1.9	2.0
B4	1.0	0.8	0.6	2.4	3.1	3.0	0.0	2.8	1.1	2.1	2.1	1.9	2.6	1.6	2.3	1.9	1.9	1.1	2.1	2.1
C1	0.6	0.5	0.5	2.3	2.6	2.9	3.1	0.0	1.3	2.0	1.6	1.8	1.5	1.3	2.1	1.3	1.1	1.3	2.0	1.6
C2	2.5	2.8	3.0	2.5	3.0	2.6	1.3	1.1	0.0	2.3	1.8	2.5	3.0	2.8	2.1	2.4	2.0	3.1	2.8	2.3
C3	3.3	3.1	2.5	2.4	2.0	2.3	2.4	1.8	2.0	0.0	3.0	2.5	2.4	1.8	1.6	2.4	1.8	3.3	2.3	2.4
D1	2.0	2.1	1.9	2.1	1.6	2.3	1.6	1.4	1.6	2.6	0.0	2.1	1.9	1.5	1.8	2.3	2.0	3.3	2.1	2.3
D2	2.6	2.4	2.1	2.0	1.6	1.8	1.4	0.8	1.8	2.9	2.1	0.0	1.8	1.8	2.0	2.3	2.0	2.9	2.1	2.0
D3	1.8	2.1	2.1	2.0	2.1	2.4	1.9	1.3	2.1	1.9	1.9	2.0	0.0	2.1	2.3	1.9	1.4	2.8	2.0	2.1
D4	2.3	2.6	2.9	2.9	3.0	3.1	0.9	0.9	2.5	2.4	1.9	2.0	2.3	0.0	2.6	2.4	1.5	2.6	1.9	2.0
E1	2.4	2.3	2.6	2.3	2.4	2.3	1.6	1.1	1.8	1.9	1.9	2.4	2.9	2.5	0.0	1.9	1.8	1.1	2.1	2.1
E2	2.8	2.9	2.3	1.3	1.8	1.6	1.5	1.1	2.5	1.9	2.0	2.0	2.4	1.9	2.6	0.0	3.0	1.3	2.0	1.6
E3	2.5	2.8	1.4	1.3	1.4	1.1	1.5	1.1	1.5	2.1	1.9	1.8	2.0	1.3	1.6	2.0	0.0	2.8	2.0	2.1
F1	2.0	2.5	2.4	1.8	1.4	1.5	2.9	2.1	2.0	2.6	2.4	2.1	2.0	1.6	1.8	1.4	0.8	0.0	2.9	2.1
F2	2.0	2.5	2.4	2.1	1.8	1.1	2.8	2.0	2.1	1.6	1.1	1.8	1.9	1.9	2.4	1.6	1.1	1.8	0.0	1.9
F3	2.6	2.4	2.1	2.0	1.6	1.8	1.4	0.8	1.8	2.9	2.1	1.6	1.1	1.8	1.9	1.9	2.4	2.0	2.3	0.0

Table A2. Normalized direct-relation matrix *X*

	A1	A2	A3	B1	B2	B3	B4	C1	C2	C3	D1	D2	D3	D4	E1	E2	E3	F1	F2	F3
A1	0.000	0.069	0.069	0.000	0.053	0.057	0.030	0.026	0.063	0.057	0.046	0.071	0.042	0.053	0.042	0.063	0.061	0.063	0.057	0.046
A2	0.071	0.000	0.069	0.046	0.061	0.059	0.028	0.026	0.067	0.046	0.048	0.071	0.048	0.057	0.040	0.051	0.051	0.067	0.046	0.048
A3	0.063	0.063	0.000	0.042	0.059	0.048	0.022	0.020	0.067	0.042	0.046	0.071	0.046	0.051	0.038	0.053	0.048	0.067	0.042	0.046
B1	0.036	0.038	0.048	0.000	0.069	0.063	0.057	0.040	0.059	0.042	0.040	0.040	0.051	0.048	0.036	0.028	0.030	0.059	0.042	0.040
B2	0.036	0.046	0.057	0.057	0.000	0.053	0.057	0.038	0.057	0.040	0.042	0.040	0.051	0.048	0.042	0.036	0.022	0.057	0.040	0.042
B3	0.040	0.042	0.059	0.046	0.073	0.000	0.053	0.048	0.053	0.038	0.040	0.051	0.053	0.051	0.051	0.042	0.038	0.053	0.038	0.040
B4	0.020	0.016	0.012	0.048	0.063	0.061	0.000	0.057	0.022	0.042	0.042	0.038	0.053	0.032	0.046	0.038	0.038	0.022	0.042	0.042
C1	0.012	0.010	0.010	0.046	0.053	0.059	0.063	0.000	0.026	0.040	0.032	0.036	0.030	0.026	0.042	0.026	0.022	0.026	0.040	0.032
C2	0.051	0.057	0.061	0.051	0.061	0.053	0.026	0.022	0.000	0.046	0.036	0.051	0.061	0.057	0.042	0.048	0.040	0.063	0.057	0.046
C3	0.067	0.063	0.051	0.048	0.040	0.046	0.048	0.036	0.040	0.000	0.061	0.051	0.048	0.036	0.032	0.048	0.036	0.067	0.046	0.048
D1	0.040	0.042	0.038	0.042	0.032	0.046	0.032	0.028	0.032	0.053	0.000	0.042	0.038	0.030	0.036	0.046	0.040	0.067	0.042	0.046
D2	0.053	0.048	0.042	0.040	0.032	0.036	0.028	0.016	0.036	0.059	0.042	0.000	0.036	0.036	0.040	0.046	0.040	0.059	0.042	0.040
D3	0.036	0.042	0.042	0.040	0.042	0.048	0.038	0.026	0.042	0.038	0.038	0.040	0.000	0.042	0.046	0.038	0.028	0.057	0.040	0.042
D4	0.046	0.053	0.059	0.059	0.061	0.063	0.018	0.018	0.051	0.048	0.038	0.040	0.046	0.000	0.053	0.048	0.030	0.053	0.038	0.040
E1	0.048	0.046	0.053	0.046	0.048	0.046	0.032	0.022	0.036	0.038	0.038	0.048	0.059	0.051	0.000	0.038	0.036	0.022	0.042	0.042
E2	0.057	0.059	0.046	0.026	0.036	0.032	0.030	0.022	0.051	0.038	0.040	0.040	0.048	0.038	0.053	0.000	0.061	0.026	0.040	0.032
E3	0.051	0.057	0.028	0.026	0.028	0.022	0.030	0.022	0.030	0.042	0.038	0.036	0.040	0.026	0.032	0.040	0.000	0.057	0.040	0.042
F1	0.040	0.051	0.048	0.036	0.028	0.030	0.059	0.042	0.040	0.053	0.048	0.042	0.040	0.032	0.036	0.028	0.016	0.000	0.059	0.042
F2	0.040	0.051	0.048	0.042	0.036	0.022	0.057	0.040	0.042	0.032	0.022	0.036	0.038	0.038	0.048	0.032	0.022	0.036	0.000	0.038
F3	0.053	0.048	0.042	0.040	0.032	0.036	0.028	0.016	0.036	0.059	0.042	0.032	0.022	0.036	0.038	0.038	0.048	0.040	0.046	0.000

Table A3. Total-relation matrix *T*

	A1	A2	A3	B1	B2	B3	B4	C1	C2	C3	D1	D2	D3	D4	E1	E2	E3	F1	F2	F3
A1	0.249	0.325	0.320	0.224	0.304	0.299	0.236	0.188	0.304	0.297	0.269	0.318	0.282	0.276	0.267	0.286	0.261	0.333	0.294	0.273
A2	0.324	0.270	0.330	0.274	0.322	0.312	0.243	0.194	0.317	0.297	0.279	0.328	0.297	0.289	0.273	0.283	0.259	0.348	0.294	0.283
A3	0.301	0.312	0.250	0.257	0.303	0.287	0.224	0.178	0.302	0.278	0.263	0.312	0.280	0.269	0.257	0.271	0.244	0.331	0.275	0.267
B1	0.256	0.268	0.275	0.201	0.295	0.283	0.243	0.187	0.275	0.259	0.240	0.264	0.266	0.250	0.239	0.230	0.211	0.301	0.256	0.244
B2	0.255	0.275	0.281	0.254	0.230	0.273	0.241	0.184	0.272	0.256	0.241	0.263	0.265	0.249	0.243	0.237	0.203	0.298	0.254	0.245
B3	0.269	0.282	0.293	0.254	0.308	0.233	0.246	0.200	0.278	0.264	0.249	0.283	0.277	0.260	0.260	0.252	0.226	0.305	0.262	0.253
B4	0.204	0.208	0.203	0.215	0.251	0.244	0.159	0.178	0.204	0.222	0.209	0.223	0.232	0.201	0.215	0.206	0.188	0.226	0.220	0.212
C1	0.171	0.177	0.175	0.191	0.218	0.218	0.198	0.109	0.183	0.197	0.177	0.197	0.188	0.173	0.189	0.172	0.153	0.202	0.195	0.180
C2	0.287	0.304	0.304	0.263	0.303	0.288	0.227	0.179	0.237	0.278	0.251	0.290	0.291	0.273	0.259	0.264	0.234	0.323	0.285	0.265
C3	0.297	0.304	0.289	0.256	0.280	0.279	0.244	0.190	0.270	0.230	0.270	0.286	0.275	0.249	0.245	0.261	0.228	0.322	0.272	0.263
D1	0.238	0.249	0.242	0.220	0.236	0.243	0.200	0.160	0.228	0.246	0.181	0.243	0.232	0.212	0.217	0.226	0.202	0.283	0.234	0.228
D2	0.252	0.257	0.248	0.218	0.238	0.235	0.197	0.149	0.234	0.253	0.223	0.204	0.231	0.219	0.222	0.228	0.204	0.278	0.236	0.224
D3	0.233	0.248	0.246	0.218	0.246	0.245	0.205	0.157	0.237	0.232	0.217	0.240	0.195	0.223	0.226	0.218	0.190	0.273	0.232	0.224
D4	0.269	0.285	0.288	0.257	0.289	0.284	0.207	0.166	0.271	0.266	0.241	0.267	0.264	0.206	0.255	0.251	0.214	0.299	0.254	0.246
E1	0.252	0.260	0.263	0.230	0.259	0.251	0.204	0.157	0.239	0.239	0.223	0.255	0.257	0.237	0.188	0.226	0.204	0.250	0.240	0.231
E2	0.256	0.267	0.252	0.206	0.242	0.232	0.198	0.154	0.247	0.234	0.221	0.244	0.243	0.222	0.234	0.185	0.224	0.249	0.234	0.217
E3	0.227	0.241	0.212	0.185	0.211	0.200	0.180	0.139	0.206	0.216	0.199	0.216	0.213	0.189	0.194	0.202	0.147	0.251	0.212	0.206
F1	0.236	0.254	0.250	0.214	0.233	0.229	0.223	0.172	0.234	0.245	0.226	0.242	0.233	0.213	0.216	0.209	0.179	0.219	0.248	0.224
F2	0.225	0.242	0.238	0.209	0.229	0.210	0.211	0.162	0.225	0.215	0.191	0.225	0.220	0.208	0.217	0.202	0.175	0.241	0.181	0.210
F3	0.243	0.248	0.239	0.210	0.229	0.226	0.189	0.142	0.225	0.244	0.215	0.226	0.209	0.211	0.211	0.213	0.204	0.251	0.230	0.177