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From Perception to Practice: An Orgaware-Centred Framework (the IDEA Architecture) for Institutionalising Operational Research and AI in Indian Defence Procurement

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Abstract

Operational Research (OR) and Artificial Intelligence (AI) are widely endorsed as decision-support tools for India's Atmanirbhar Bharat defence indigenisation programme, yet adoption lags endorsement. This paper develops the IDEA (Indigenisation Decision-support Ecosystem Architecture), a three-tier framework linking six orgaware-related gaps — organisational, rather than purely technical, barriers to OR/AI adoption — to specific decision-support mechanisms. The framework is grounded in survey evidence from 392 Indian defence practitioners (Armed Forces, Ministry of Defence, Defence Public Sector Undertakings, and private industry).

The design of the architecture is motivated by three empirical findings: A large-effect regression result demonstrating that 31.7% ($f^2 = .464$) of the variance in satisfaction with the Armed Forces is explained by collaboration preferences plus policy support; a chi-square test that shows that there is a significant difference in collaboration preferences based on type of organisation ($\chi^2(9) = 18.41$, $p = .031$); and a finding that leadership support is the most often mentioned adoption factor (76.0% of the respondents). The IDEA Architecture is based on these findings, and presents a diagnostic tier (four structural gaps), a decision-support tier (six OR/AI mechanisms) and a multi-track collaborative ecosystem tier with a proposed OR/AI Centre of Excellence (CoE) that has binding recommendation authority. The paper is clear on the issues that have been validated by survey evidence and the remaining issues that have not been tested, but are rather research and institutional commitments.

Keywords: Operational research; artificial intelligence; decision support systems; defence indigenisation; institutional design; orgaware; India

1. Introduction

A companion survey of 392 Indian defence practitioners establishes that OR/AI readiness is positively associated with indigenisation effectiveness and, combined with policy support, strongly predicts Armed Forces satisfaction — but that this readiness is predominantly attitudinal: endorsement of OR/AI's value ($M \approx 3.54$–3.92 across relevant items) substantially exceeds active use ($M \approx 2.30$–2.55). The present paper asks a design question that follows directly from that empirical gap: what institutional architecture would convert attitudinal readiness into institutionalised practice?

We argue that the barrier is not primarily methodological — OR and AI techniques suitable for defence procurement decisions are well established in the literature — but organisational. We apply Kharbanda and Jain's (1997) findings of Indian DPSU technology absorption and subsequent findings to the term ‘orgaware' for the organisational conditions (clear decision rights, reliable data infrastructure, a culture that tolerates model-based recommendations) that OR/AI tools implicitly rely on and for which these conditions are often missing in this institutional environment. There is now, on this reading, an orgaware gap in lower adoption of OR/AI, which is wearing a "method's" mask. This paper has two contributions. First, it relates six distinctively identified gaps in OR in the context of the orgaware to six distinct OR/AI decision-support mechanisms, not according to any academic discipline, but according to the point at which a practitioner finds himself in a decision situation. Second, it offers an institutional architecture (IDEA Architecture) that puts these outputs of mapping into practice, with a diagnostic tier, a decision-support tier, and a collaborative ecosystem tier, and details the

governance architecture (an OR/AI Centre of Excellence) necessary to take a mapping to a binding procurement decision..

2. Conceptual Framework: Mapping Orgaware Gaps to OR/AI Mechanisms

Table 1 presents six pairings of gap and decision points, starting from the most procedurally concrete (from prototype to procurement order) to the most institutionally abstract (whether or not the institutionalisation of OR/AI decision support exists). Every row connects an OR/AI gap that a practitioner encounters to the OR/AI mechanism that is able to solve it.

Table 1. Integrated Framework Mapping Orgaware Gaps to OR/AI Decision-Support Mechanisms.

Orgaware Gap	Decision Point	OR/AI Mechanism
Prototype-to-procurement absorption bottleneck	Whether to convert an iDEX/ADITI prototype into a procurement order, and on what terms	AHP/TOPSIS multi-criteria evaluation of indigenous-content depth, delivery-timeline risk, and lifecycle cost
DPSU patent concentration and thin R&D base	Where to direct scarce R&D investment across competing technology pathways	MCDM-based technology-pathway prioritisation; portfolio optimisation under budget constraints
Vendor/OEM selection under DAP 2026	Which vendor or technology-transfer partner to select for a given platform	AHP/TOPSIS vendor-evaluation model built on multi-criteria supplier-selection literature
DPSU production-line modernisation	How to sequence and size production-line automation investment	Discrete-event and system-dynamics simulation of throughput under alternative scenarios
sUAS/equipment maintenance ecosystem gaps	When and how to service indigenised equipment to sustain AF satisfaction	AI-based predictive-maintenance models trained on maintenance-log data
OR/AI treated as technology to indigenise, not decision support to apply	Whether and how to institutionalise OR/AI decision support within MoD/DPSU processes	Integrated framework synthesising all preceding mechanisms; expert-panel validation

There are two elements to this mapping that need to be highlighted. First, the mechanisms are not standalone: the vendor-selection model in row three includes some criteria which are also included in the prototype-to-procurement model in row one; and the predictive-maintenance model in row five provides exactly the equipment-performance data that would be used in the technology-pathway prioritisation in row two. Second, the sixth row of the table, institutionalising OR/AI decision support, is a different category from the first five rows which are about a specific pathway, vendor or production line; and no MCDM or simulation model can determine on its own whether an institution will be willing to embrace it or not.

3. Empirical Motivation

The architecture presented in Section 4 is inspired by three results of the accompanying survey (N = 392; methodology described separately).

3.1 Institutional Support Dominates Technical Readiness

An ORAI and a Policy Support Index predicting Armed Forces Satisfaction was found to be significant, $F(2, 389) = 90.28$, $p < .001$, $R^2 = .317$, $f^2 = .464$ (large effect). There was no multicollinearity between the two predictors (VIF = 1.158) nor was there significant autocorrelation (Durban Watson = 1.862). The higher the

coefficient of policy support, the more important institutional support is to satisfaction of Armed Forces, directly influencing this paper's deliberate institutional design focus, in addition to using analysis.

3.2 Collaboration Preferences Differ Significantly by Organisation Type

The chi square test of independence between the preferred type of collaboration and the type of organisation was significant $\chi^2(9) = 18.41$, $p = .031$. Also, there was a strong correlation between the effectiveness of the DSS integration and the perceived importance of OR/AI ($r = .618$, $p < .001$) and the perceived usefulness ($r = .521$, $p < .001$). The differing priorities for collaboration across stakeholder communities is one major result from which the multi-track ecosystem design in Section 4.3 is directly motivated — because if there was one way to collaborate it would systematically underserve some constituency.

3.3 Leadership Support Is the Primary Adoption Factor

The four candidate DSS adoption factors ranked in order of importance to respondents were: training/familiarity, perceived utility, and leadership support (76.0% of respondents selected this factor), and workflow compatibility. In isolation, 68.4% said that shared data-infrastructure principles should be agreed upon, and 31.6% said that they should not be agreed upon — suggesting that data-sharing can't be taken for granted and must be negotiated through a series of steps that erode trust. These findings, combined, name a new problem that may be seen as a constraint to adoption: leadership mandate and governed data-sharing, not technical training.

4. The IDEA Architecture

The IDEA (Indigenisation Decision-support Ecosystem Architecture) organises the Table 1 mapping into three tiers — diagnostic, decision-support, and ecosystem — shown in Figure 1.

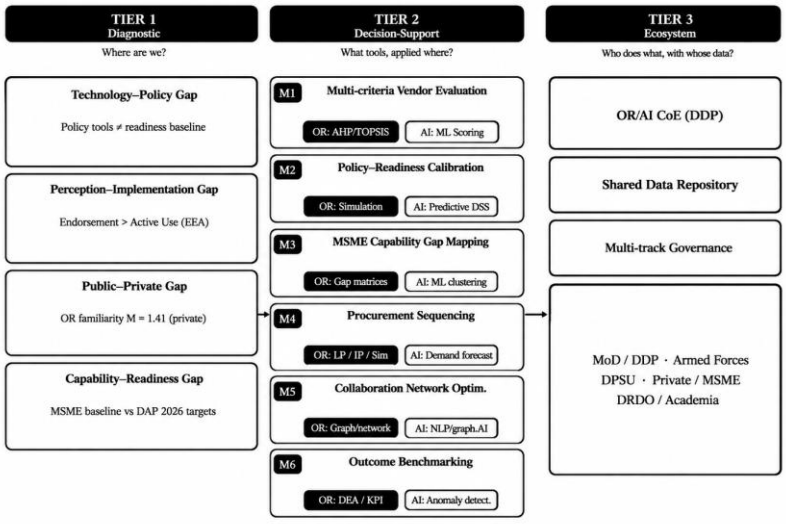


Figure 1. The IDEA Architecture — Three-Tier Overview (Diagnostic → Decision-Support → Ecosystem).

4.1 Tier 1: Diagnostic

Tier 1 is founded on four structural gaps hypothesized by the survey evidence as findings, rather than theory: technology–policy gap (M = 3.54–3.92 vs. M = 2.30–2.55), perception–implementation gap (M = 3.54–3.92 vs. M = 2.30–2.55), public–private gap (M = 2.57, with private-industry OR/AI familiarity lagging the Armed-Forces-weighted sample mean), and capability–readiness gap (M = 2.57, with OR/AI readiness lagging across

all sub-groups). It is not aspirational technology targets, but rather these four gaps are what will be addressed with Tiers 2 and 3.

4.2 Tier 2: Decision Support — Six Mechanisms

Tier 2 restates Table 1's six mechanisms with OR and AI components separated, because practitioners have measurably different relationships with the two toolkits: OR tools (AHP, simulation, optimisation) require structured data and expert judgement and are the more accessible entry point, while AI tools (ML scoring, NLP, anomaly detection) require larger datasets and specialist maintenance capability. A capacity-building pathway that conflates the two will be too demanding at entry for the MSMEs that most need it.

Mechanism 2 (policy–readiness calibration) carries particular empirical weight: it is the mechanism most directly connected to the H2 finding (DSS + policy support, $f^2 = .464$), and the leadership-adoption bottleneck (76.0%) is most critical to its success, since a predictive DSS dashboard without a leadership mandate to act on its outputs functions as a monitoring tool rather than a decision-support tool. Mechanism 5 (collaboration network optimisation) is motivated directly by the H4 chi-square finding: network analysis is used to identify structural holes — MSME–DPSU pairings that would generate high indigenisation returns but are not currently connected — rather than mandating a uniform collaboration format that the H4 result shows would not fit all organisation types equally.

4.3 Tier 3: Collaborative Ecosystem

Tier 3 is single-track, with a policy calibration and procurement sequencing track, direct to the H4 finding that the preferences for collaboration vary greatly by organization type ($\chi^2(9) = 18.41$, $p = .031$); a DPSU and Armed Forces track, starting with prototype-to-procurement decisions and ending with end-user validation; a private-industry Tier-1 track, beginning with vendor evaluation and continuing with participation in the collaboration network; and an MSME track, beginning with capability mapping (Mechanism 3) and progressing through the other mechanisms as analytical capacity expands. The tracks don't work as silos, instead using a shared data infrastructure. The CI is underpinned by an OR/AI Centre of Excellence (CoE) under the direct control of DDP. It has been designed with regard to the 76.0% leadership-commitment finding, providing the CoE with binding authority to make recommendations on a specific set of procurement decision types, as opposed to advisory; that is, turning the analytical output into institutional mandate, which the regression evidence in Section 3.1 suggests is what is missing between OR/AI readiness and measurable outcomes. The CoE also contains the common data repository, which is part of the 68.4% / 31.6% endorsement of data-sharing by the MoD / DDP, and regulates access to the data via protocols that gradually foster trust in the data repository rather than simply taking it for granted (MoD / anonymised benchmarks for MSMEs).

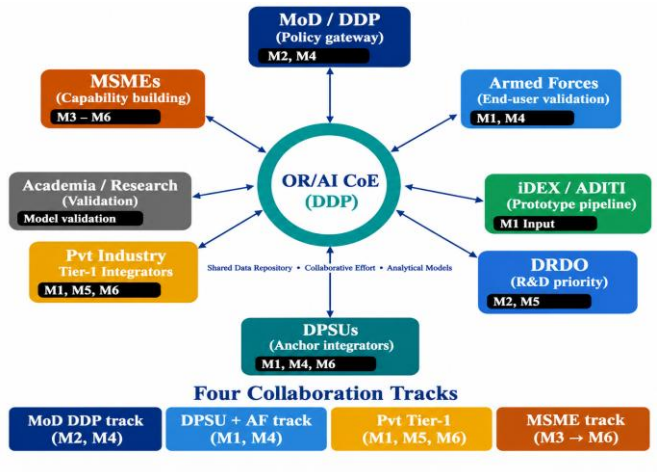


Figure 2. Tier 3 Collaborative Ecosystem — OR/AI Centre of Excellence as Hub with Multi-Track Actor Architecture.

Eight actor types are connected to the ecosystem, and four tracks for collaboration are identified that connect them to the CoE (figure 2). MoD/DDP and Armed Forces sit on their respective tracks, with different weightage, with DPSUs on the bridge between prototype and procurement; and Tier-1 private integrators and MSMEs are deliberately kept on separate tracks – the capability-readiness gap identified in Section 3.3 makes it unsuitable for the latter to jump straight to entry into the procurement process, while the former may not know exactly what to build at entry.

4.4 Implementation Sequencing

Translating the architecture into practice is sequenced rather than simultaneous. The highest-priority step is institutional: establishing the CoE within DDP, with a formal order specifying which procurement categories require its analytical input before a decision can proceed. This is deliberately prioritised ahead of the technical build-out of individual mechanisms, because the H2 finding indicates that mechanisms deployed without institutional mandate will under-perform relative to mechanisms deployed with it. Table 2 summarises the sequencing logic for the three principal actor groups.

Table 2. Implementation Sequencing by Actor Group.

Actor	Immediate Priority	Empirical Motivation
MoD / DDP	Charter and staff the OR/AI CoE (12 months); first operational models (24 months)	H2: $f^2 = .464$; 76.0% leadership-commitment finding
DPSUs / Armed Forces	Contribute production and maintenance data to the shared repository; validate Mechanism 1 prototype-conversion criteria	Production–quality divergence (M = 4.05 vs. M = 2.71)
Private industry (Tier-1 / MSME)	Tier-1: build DEA-compatible performance tracking. MSME: complete Mechanism 3 capability self-assessment before formal evaluation	Private-industry OR familiarity M = 1.41, trailing the sample mean

This sequencing treats institutional mandate as the rate-limiting step and technical capability-building as following from it, rather than the reverse — the inverse of how OR/AI adoption programmes are conventionally sequenced in the practitioner literature, and the architecture's central claim.

5. Discussion: What Is Validated and What Remains Outstanding

Intellectual honesty about validation status is itself part of this paper's contribution. The diagnostic tier rests on confirmed survey findings (Section 3) and is, in that sense, empirically grounded. The decision-support tier's mechanism assignments are theoretically motivated by the OR/MCDM and AI-in-manufacturing literatures (Saaty, 1980; Hwang & Yoon, 1981; Weber et al., 1991; Banks et al., 2010) and by the Table 1 gap-mapping logic, but the mechanisms themselves — whether an AHP hierarchy for representative DAP 2026 vendor-selection cases actually achieves a consistency ratio below 0.1, whether a production-line simulation surfaces constraints practitioner judgement misses — have not been built and run on representative procurement data. The ecosystem tier's CoE governance proposal has not been tested against an expert Delphi panel. These are stated as outstanding research and institutional obligations, not as a weakness this paper obscures: a framework that claimed mechanism-level or institutional validation it had not performed would be the more serious error.

The survey evidence does confirm the empirical motivation and institutional design rationale for the architecture: the H2 result suggests that institutional mandate is more important than technical readiness and the H4 result supports a multi-track (not uniform) ecosystem design, and the 76.0% result for leadership implies that the proposed CoE should have binding, not advisory, authority. The modelling and validation of the mechanism level is the direct next step for this paper, as in Kharbanda and Jain (1997), the technology was not the

constraint on the indigenisation of technology in industry, but rather the capacity of the organisation to absorb the technology.

6. Conclusion

The hurdles for the adoption of OR/AI within India's defence indigenisation ecosystem aren't as much methodological as the organizational prepositions, usually taken for granted from leadership mandate, data sharing that's governed, and decision rights, that are part of the OR/AI. The IDEA Architecture takes this diagnosis and turns it into a 3-tiered design: diagnostic tier based on validated survey findings, decision-support tier comprising six design mechanisms mapped to specific orgaware gaps, and ecosystem tier with an OR/AI Centre of Excellence having binding recommendation authority. The architecture's most crucial design choice, prioritizing mandate over technical training as the policy tool that will be adopted, is a direct outcome of the fact that policy support was more important than OR/AI readiness to Armed Forces satisfaction. The architecture now relies on two things which this paper has been clear about not being done: mechanism-level modelling of real cases of procurement, and assessment of this architecture for use by expert panels in practice.

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