International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1

Operational Research and Artificial Intelligence Readiness as Predictors of Indigenisation Effectiveness and Armed Forces Satisfaction: Survey Evidence from India's Defence Ecosystem (N = 392)

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Abstract

India's Atmanirbhar Bharat defence indigenisation programme has substantially increased domestic production volumes, yet whether Operational Research (OR) and Artificial Intelligence (AI) decision-support methods are being institutionalised to support this transition remains empirically underexamined. This study surveyed 392 practitioners across the Armed Forces, Ministry of Defence (MoD), Defence Public Sector Undertakings (DPSUs), and private defence industry to test whether OR/AI readiness predicts indigenisation effectiveness and Armed Forces (AF) satisfaction. Composite constructs were built from a 93-item, five-point Likert instrument and checked for reliability (Cronbach's α = .584–.847) and factor structure (two-factor exploratory factor analysis, 66.1% variance explained). OR/AI readiness significantly predicted indigenisation effectiveness (r = .369, $p < .001$, f^2 = .158) and, combined with policy support, explained 31.7% of the variance in AF satisfaction (f^2 = .464, large effect). However, OR/AI readiness explained only 7.3% of variance in quantifiable production-quality outcomes (f^2 = .079), and a two-factor structure separating attitudinal endorsement ($M \approx 3.54$–3.92) from active use ($M \approx 2.30$–2.55) indicates a substantial perception–adoption gap. Leadership support was the most frequently endorsed adoption factor (76.0% of respondents). These findings suggest that OR/AI's contribution to indigenisation is currently attitudinal rather than operational, and that institutionalisation — not individual familiarity — is the binding constraint on converting analytical readiness into measurable outcomes.

This paper presents the results of a survey conducted with 392 defence-sector practitioners which tested three hypotheses: (H1) OR/AI readiness is a predictor of perceived effectiveness of indigenisation; (H2) OR/AI readiness and policy support are predictors of satisfaction with the Armed Forces; and (H3) OR/AI readiness is a predictor of measurable production, reliability and economic outcomes. The findings call for a differentiation between OR/AI as an approved attitude and OR/AI as an institutionalised practice which is proposed in the discussion.

Keywords: operational research; artificial intelligence; defence indigenisation; Atmanirbhar Bharat; decision support systems; survey research; India

1. Introduction

The Atmanirbhar Bharat (Self-reliant India) policy framework has been the catalyst for the Defence indigenisation programme, which has clearly led to an increase in the manufacture of products in the country in the last ten years and has been carried out through the Defence Acquisition Procedure (DAP) 2026. However, production volume is only a partial measure of the success of a programme as whether indigenous products are as reliable and as performant as imported products, and whether the analytical tools (Operational Research (OR) and Artificial Intelligence (AI) required for closing the gap are being implemented in practice are empirical questions, which official production statistics cannot answer. In the policy and practitioner literature, there are broad expectations that OR techniques (such as multi-criteria decision-making, simulation, optimisation) and AI applications (such as predictive maintenance, quality-control classification, design optimisation) provide just this capability. Among the various tools available, the less know is whether these are actually adopted by the practitioners within the Indian defence ecosystem — Armed Forces personnel, MoD officials, DPSU managers and private industry — and whether their adoption is correlated with positive indigenisation outcomes or satisfaction of the Armed Forces, the key end-user community.

2. Literature Review

Indian defence indigenisation research has documented a persistent tendency to build production infrastructure ahead of design and quality-assurance capability (Jain & Kharbanda, 2003; Ghosh, 2016), a pattern this study's production–quality divergence finding (Section 4) reproduces with current survey data. Separately, a large OR and MCDM (multi-criteria decision-making) literature establishes the methodological toolkit — AHP, TOPSIS, CoCoSo, and related techniques — for structuring the trade-offs (cost, indigenous-content depth, delivery risk) that characterise defence procurement decisions (Yazdani et al., 2019; Abdel-Basset et al., 2019; Boukrouh et al., 2024).

A parallel AI-in-manufacturing literature documents predictive maintenance, quality-control classification, and design-optimisation applications as mature, transferable capabilities (Aspeteg et al., 2026), while supply-chain and defence-enterprise research highlights the institutional and data-sharing barriers that constrain their adoption in late-industrialising defence sectors specifically (Anderson & Luiz, 2025). The OR literature also notes the different aspects of methodological availability vs. organisational adoption, as seen in hybrid-simulation reviews (Brailsford et al., 2019), an issue reinforced by the empirical findings of this paper. The literature has not provided a large sample empirical analysis with multiple stakeholders to validate the relationship between OR/AI readiness and indigenisation outcomes in the Indian defence industry specifically. This study goes right to the source of that void.

3. Methodology

3.1 Research Design and Sample

The design of this study was a cross sectional survey. The structured instrument comprising 93 questions with three substantive sections (I) indigenisation impact, (II) industry capability and satisfaction of Armed Forces, and (III) familiarity, use of, and need for OR/AI in industry decision making) as well as a demographic block was administered to key practitioners across the Indian defence ecosystem. After screening N = 392 valid responses were retained. Table 1 presents the results of the achieved sample.

Table 1. Demographic and Professional Profile of Respondents (N = 392).

Characteristic	Category	n	%
Gender	Male	386	98.5
	Female	6	1.5
Age	35–45 years	189	48.2
	25–35 years	83	21.2
	45–55 years	78	19.9
Education	Postgraduate	253	64.5
	Graduate	126	32.1
Experience	10–20 years	187	47.7
	20–30 years	107	27.3
Organisation type	Armed Forces (serving)	291	74.2
	Private industry	46	11.7
	Armed Forces (retired)	28	7.1
	MoD / Government	11	2.8
	DPSU	3	0.8

Of the 319 respondents, 81.4% are Armed Forces personnel (serving and retired combined) and are therefore Armed Forces-weighted; this is appropriate, since Armed Forces satisfaction is both a key research question and the population from which most respondents come — but could limit the usefulness of reports of the smaller sub-samples of respondents from the MoD (n = 11) and DPSU (n = 3), which are reportable descriptively but interpreted with caution.

3.2 Measures and Composite Constructs

Six composite indices were computed as row means across their constituent five-point Likert items, with reverse-scoring applied where the original item direction was unfavourable: the Indigenisation Effectiveness

Index (IEI, 9 items), Technological Capability Index (TCI, 3 items), Armed Forces Satisfaction Index (SAT, 3 items), OR/AI Readiness Index (ORAI, 6 items), Policy Support Index (PSI, 5 items), and Operational Challenges Index (OCI, 4 items). Internal consistency and descriptive statistics are reported in Table 2.

Table 2. Reliability and Descriptive Statistics for Composite Constructs (N = 392).

Construct	Items	α	M	SD
Indigenisation Effectiveness Index (IEI)	9	.812	3.61	0.46
Technological Capability Index (TCI)	3	.771	2.70	0.90
Armed Forces Satisfaction Index (SAT)	3	.847	2.67	0.75
OR/AI Readiness Index (ORAI)	6	.779	2.57	0.57
Policy Support Index (PSI)	5	.584	3.50	0.61
Operational Challenges Index (OCI)	4	.586	3.47	0.58

Four of the six constructs are greater than the conventional threshold of $\alpha = .70$ (Nunnally, 1978), while PSI and OCI are less than that threshold ($\alpha = .584$ and .586) as the constructs are thematic, and an exploratory area of research where validated scales related to indigenisation in the Indian defence sector are not yet available (Cortina, 1993). These two indices are not used to make inferences, but are used descriptively. Exploratory factor analysis (KMO = .733, Bartlett's $\chi^2(15) = 720.875$, $p < .001$) was then conducted to further examine the OR/AI Readiness Index items for their construct validity. The two factor solution accounted for 66.1% of variance; Factor 1 ("Active Use," 47.0%) was related to familiarity, usage, and training level with OR/AI; Factor 2 ("Endorsement," 19.1%) related to training importance and OR/AI familiarity. The separation between attitudinal endorsement and actual use is a direct motivator of the perception–adoption gap mentioned above in Section 5.

3.3 Data Analysis Procedures

All of the hypotheses were tested using simple linear regression and Pearson correlation: H1, H3; multiple OLS regression (ORAI and PSI predicting SAT): H2. There was no normality assumption for items (with a Shapiro-Wilk test on a random subsample of ORAI scores ($n = 50$), $W = .546$, $p < .001$, which is an expected result for ordinal data, but not for composites (which had average scores of 3–9 items). For the multiple regression analyses, the diagnostics of multicollinearity and autocorrelation (VIF and Durbin-Watson) were calculated. All tests used $\alpha = .05$, with Cohen's (1988) f^2 conventions (small $\geq .02$, medium $\geq .15$, large $\geq .35$) reported alongside p-values

4. Results

4.1 Production–Quality Divergence

Before turning to the hypothesis tests, one descriptive finding frames their interpretation. Indigenisation's impact on production capability is rated positively by 93.6% of respondents ($M = 4.05$, $SD = 0.56$), but indigenous products compared to imported equivalents on reliability and performance are rated well below the scale midpoint ($M = 2.71$, $SD = 0.75$). This production–quality divergence recurs throughout the dataset and is consistent with prior observations that Indian defence policy has built production volume ahead of design-authority capability (Jain & Kharbanda, 2003; Ghosh, 2016).

4.2 Hypothesis Tests

H1 (OR/AI readiness → indigenisation effectiveness): OR/AI readiness significantly predicted indigenisation effectiveness ($r = .369$, $p < .001$), explaining 13.6% of variance ($R^2 = .136$; $f^2 = .158$, medium effect). H1 is supported.

H2 (OR/AI readiness + policy support → AF satisfaction): the combined model was significant, $F(2, 389) = 90.28$, $p < .001$, explaining 31.7% of variance in AF satisfaction ($R^2 = .317$; $f^2 = .464$, large effect). Both

predictors contributed independently (ORAI: β = 0.388, p < .001; PSI: β = 0.624, p < .001). Diagnostics ruled out multicollinearity (VIF = 1.158) and autocorrelation (Durbin-Watson = 1.862). H2 is supported.

H3 (OR/AI readiness → quantifiable outcomes): OR/AI readiness correlated significantly but weakly with a quantifiable-outcomes index (quality change, reliability vs. imports, economic impact): r = .270, p < .001, R^2 = .073 (f^2 = .079, small effect). H3 is partially supported.

Table 3. Summary of Hypothesis Testing Results (N = 392).

Hypothesis	Key Result	Effect Size	Variance Explained	Outcome
H1: ORAI → IEI	r = .369, p < .001	f^2 = .158 (medium)	13.6%	Supported
H2: ORAI + PSI → SAT	R^2 = .317, F = 90.28, p < .001	f^2 = .464 (large)	31.7%	Supported
H3: ORAI → Outcomes	r = .270, p < .001	f^2 = .079 (small)	7.3%	Partially supported

4.3 The Perception–Adoption Gap

The EFA two-factor structure reported in Section 3.2 is substantively reflected in the item-level means: OR/AI familiarity and usage items average M = 2.30–2.55, while perceived importance and prospective usefulness items average M = 3.54–3.98. The sentiment was far stronger among respondents for valuing OR/AI than in terms of their use of it. The most common factors that respondents see as critical to the adoption of Decision Support System (DSS) are leadership support (76.0%), training/familiarity (70.4%), perceived utility (64.0%), and workflow compatibility (55.6%) as shown in Figure 1.

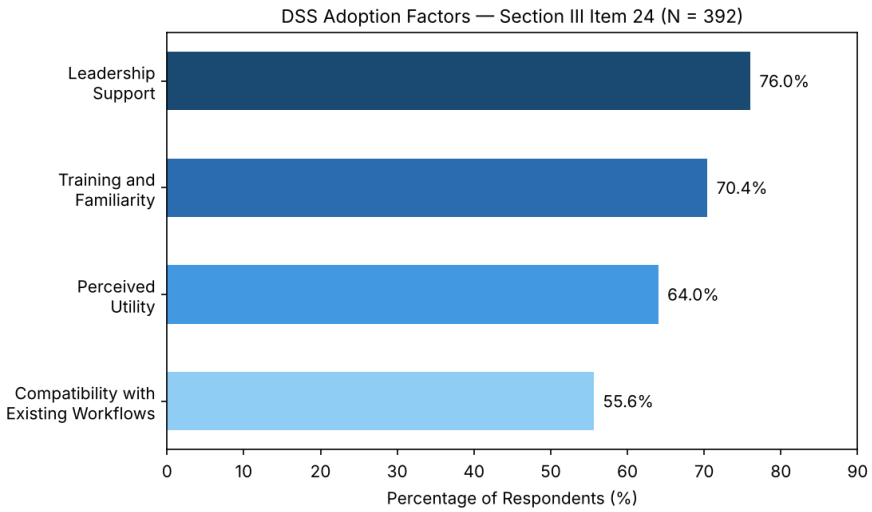


Figure 1. DSS Adoption Factors Ranked by Respondent Endorsement (N = 392).

This ordering indicates that the adoption gap is organisational rather than technical: practitioners are not primarily held back by a lack of confidence in OR/AI methods but by the absence of institutional mandate to use them.

5. Discussion

The discussion is organised by three findings. First, the indigenisation effectiveness is partially explained by OR/AI readiness (H1: f^2 = .158) and, on its own, is a strong driver of Armed Forces satisfaction (H2: f^2 = .464) along with policy support. The results of the H2 effect size are approximately three times that of the H1, meaning that the effect of OR/AI is much greater when combined with institutional policy support than when used alone, as supported by this study's overall conclusion that OR/AI effect on outcomes is dependent on

institutionalisation and not solely on individual readiness. Second, the least diagnostic value in the data set is the weak H3 result ($f^2 = .079$). If improving the production quality and reliability were straightforward to do in the realm of OR/AI, H3 should exhibit a similar effect size to H1 or H2.It does not. Quality parity with imports (M = 2.71) and delivery timelines are, in the language of this study, harder-edged outcomes that general attitudinal readiness does not move, whereas perception-level constructs like indigenisation effectiveness and AF satisfaction are more responsive to it. This is consistent with the two-factor EFA structure: the 'Active Use' factor that would be expected to drive measurable outcomes is the lower-scoring of the two factors ($M \approx 2.30$–2.55), while the 'Endorsement' factor that drives the perception-level H1/H2 results is higher ($M \approx 3.54$–3.92).

Third, the leadership-support finding (76.0% of respondents citing it as the primary DSS adoption factor) identifies where the institutionalisation this study's regression results call for would need to originate. This is not a resourcing or training problem in the first instance — training/familiarity ranks second at 70.4% — but a governance problem: OR/AI outputs without a leadership mandate to act on them function as analysis, not decision support.

These results qualify, rather than contradict, the policy assumption that OR/AI adoption will follow from exposure and training. Exposure (endorsement) is already comparatively high; it is institutional use (active practice) that lags, and the data indicate leadership mandate, not technical capability, as the more binding constraint on closing that gap.

6. Limitations

The sample is Armed-Forces-weighted (81.4%) by design, and the MoD (n = 11) and DPSU (n = 3) sub-samples are too small to support reliable category-level inference; findings for these groups should be read as indicative. Two composite constructs (PSI, OCI) fall below the conventional $\alpha = .70$ reliability threshold and are used descriptively rather than as regression predictors beyond H2. All measures are self-reported perceptions; the H3 quantifiable-outcomes index itself consists of perceived rather than independently verified production metrics. Finally, this is a cross-sectional design: the directional language used for H1–H3 reflects the framework's theorised causal structure rather than demonstrated temporal precedence.

7. Conclusion and Policy Implications

Indian defence practitioners are capable of being ready for the use of OR/AI – but it is realistic rather than technical, meaning that a sense of the value of using OR/AI is outstripping their actual use – and this is what is holding them back from a measurable impact on indigenisation outcomes rather than a lack of technical confidence. It is clear from the results that there are three implications. The leadership support finding (76.0%) suggests that it would be necessary to require, instead of just encouraging, OR-based decision analysis be included in larger procurement proposals to create a meaningful difference for MoD and DDP than more investment in training. The production–quality divergence (M = 4.05 vs. M = 2.71) suggests the need to include performance–parity standards for indigenous content percentage targets with imported equivalents. The weak H3 result highlights that for future research it is important to test whether the specific OR/AI tools (AHP/TOPSIS vendor evaluation, predictive-maintenance modelling) actually produce decision-relevant outputs when they are actually built and run on representative procurement data, which is what this survey-based design cannot provide.

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