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The Role of Emerging Technologies in Indian Knowledge System for Multi-Domain Innovation

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Abstract: *The Indian Knowledge System (IKS) constitutes one of the world's oldest continuously evolving repositories of scientific, medical, agricultural, linguistic, artistic, and philosophical knowledge. In parallel, the last decade has witnessed the maturation of a cluster of emerging technologies—artificial intelligence and machine learning (AI/ML), natural language processing and large language models (NLP/LLMs), the Internet of Things (IoT), blockchain, augmented/virtual/extended reality (AR/VR/XR), and big data analytics—that offer unprecedented instruments for the documentation, validation, dissemination, and innovative extension of traditional knowledge. However, existing scholarship remains fragmented across individual technology–domain pairings, and a systematic, quantitative assessment of which technologies hold the greatest innovation potential across multiple IKS domains is lacking. This paper addresses that gap through a simulation-based multi-criteria decision-analysis (MCDA) framework. Drawing on a structured consolidation of 142 published studies (2015–2025), six emerging technologies are evaluated against six IKS application domains—Ayurveda and traditional medicine, traditional agriculture, education and pedagogy, languages and manuscripts, arts, crafts and architecture, and governance and ethics—using a hybrid Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model, followed by Monte Carlo simulation of adoption diffusion using the Bass model over a 2025–2035 horizon. Simulation results indicate that AI/ML attains the highest composite innovation-potential index (CIPI = 0.742), followed by NLP/LLMs (0.684) and big data analytics (0.623), with NLP exhibiting the single strongest technology–domain pairing in manuscript digitisation and language revitalisation (closeness coefficient = 0.86). Baseline diffusion projections suggest cumulative institutional adoption of IKS–technology integration reaching approximately 62% by 2035, with a 90% simulation interval of 48–74%. Sensitivity analysis confirms the stability of the top-three technology rankings under ±20% weight perturbation. The paper concludes with a phased integration framework and policy implications aligned with the National Education Policy (NEP) 2020 and the Digital India programme. All quantitative findings are simulation-derived and intended as decision-support estimates rather than empirical field measurements.*

Keywords: Indian Knowledge System (IKS); emerging technologies; artificial intelligence; natural language processing; multi-criteria decision analysis; Fuzzy AHP; TOPSIS; Monte Carlo simulation; Bass diffusion model; multi-domain innovation; NEP 2020; digital heritage.

I. INTRODUCTION

The Indian Knowledge System (IKS) refers to the vast, interlinked body of knowledge traditions that originated and evolved in the Indian subcontinent over several millennia, encompassing formalised disciplines such as Ayurveda, Yoga, Vrikshayurveda (plant science), Jyotisha (astronomy and mathematics), Vastu Shastra (architecture), Natyashastra (performing arts), Nyaya (logic and epistemology), and an extraordinarily rich linguistic and manuscript heritage estimated at over five million manuscripts, of which fewer than ten percent have been catalogued in digital form. Far from being a static archive, IKS represents a living epistemic ecosystem whose methods of observation, classification, and validation continue to inform contemporary practice in medicine, agriculture, wellness, design, and community governance across India and the global diaspora.

The policy environment in India has decisively repositioned IKS from the periphery to the centre of the national innovation agenda. The National Education Policy (NEP) 2020 explicitly mandates the integration of Indian knowledge traditions into curricula at all levels, and the Ministry of Education established a dedicated IKS Division within the All India Council for Technical Education (AICTE) to fund research, develop courseware, and support centres of excellence. Concurrently, missions such as Digital India, the National Mission on Manuscripts, the AYUSH digitisation initiatives including the Traditional Knowledge Digital Library (TKDL), and the BHASHINI national language technology mission have created a digital public infrastructure upon which technology-enabled IKS innovation can be constructed. This confluence of civilisational knowledge assets and state-backed digital infrastructure constitutes a rare structural opportunity for what this paper terms multi-domain innovation: the simultaneous, mutually reinforcing generation of innovative products, services, pedagogies, and governance instruments across several IKS domains through shared technological capabilities.

At the same time, a cluster of emerging technologies has crossed critical thresholds of capability and affordability. Artificial intelligence and machine learning now support reliable image classification, predictive modelling, and knowledge-graph construction at scale; transformer-based natural language processing and large language models have made high-quality optical character recognition (OCR), machine translation, and semantic search feasible for Sanskrit, Prakrit, Pali, Persian, and regional-language corpora that were previously computationally intractable; Internet of Things sensor networks permit continuous monitoring of soil, climate, and crop conditions relevant to traditional agro-ecological practices; blockchain offers tamper-evident provenance registers for traditional knowledge holders, geographical indications, and artisan supply chains; augmented, virtual, and extended reality enable immersive pedagogy and virtual heritage reconstruction; and big data analytics supports the integration and mining of heterogeneous IKS corpora, clinical registries, and cultural datasets.

Despite a rapidly expanding literature, three gaps persist. First, existing studies are overwhelmingly siloed: AI for Ayurvedic diagnostics, NLP for Sanskrit OCR, blockchain for geographical indications, and AR/VR for heritage tourism are each investigated in isolation, without a common evaluative framework that would allow policymakers and institutional leaders to compare technologies on a like-for-like basis across domains. Second, quantitative decision-support evidence is scarce; most contributions are conceptual, descriptive, or based on small pilots, and very few employ structured multi-criteria methods to rank technology–domain combinations. Third, the temporal dynamics of adoption remain unexamined: there is little modelling of how quickly IKS–technology integration might plausibly diffuse through India's higher-education institutions, AYUSH facilities, agricultural extension systems, and cultural bodies, and under what parameter assumptions.

This paper responds to these gaps with three interlocking contributions. First, it consolidates the fragmented literature into a unified two-dimensional evaluation space of six emerging technologies (T1–T6) and six IKS application domains (D1–D6), assessed against a six-criterion framework spanning technical readiness, domain fit, scalability, cultural-fidelity preservation, cost feasibility, and policy alignment. Second, it operationalises this space through a hybrid Fuzzy AHP–TOPSIS model in which criterion weights are elicited from triangular fuzzy pairwise comparison matrices synthesised from the consolidated literature, and thirty-six technology–domain pairs are scored via TOPSIS closeness coefficients. Third, it embeds the static ranking in a dynamic setting by projecting adoption diffusion with a Bass model subjected to Monte Carlo simulation (10,000 runs) over the 2025–2035 horizon, together with sensitivity analysis of criterion weights. The study is explicitly simulation-based: all numerical outputs are model-generated decision-support estimates grounded in literature-derived parameters, not empirical field survey measurements, and are reported as such throughout.

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The remainder of the paper is organised as follows. Section 2 reviews related work across the six technology streams and identifies the research gap. Section 3 details the research methodology, including the ten-phase workflow, the Fuzzy AHP–TOPSIS formulation, and the Monte Carlo Bass diffusion design. Section 4 presents and discusses the simulation results with supporting tables and figures. Section 5 concludes with theoretical and policy implications, limitations, and directions for future work.

II. RELATED WORKS

Research at the intersection of emerging technologies and the Indian Knowledge System has grown markedly since 2015, propelled by policy attention following NEP 2020 and by the general maturation of AI toolchains. This section organises the literature along the six technology streams examined in this study and closes by articulating the research gap.

2.1 Artificial Intelligence and Machine Learning in Traditional Medicine and Beyond

The most developed strand applies AI/ML to Ayurveda and allied AYUSH systems. Studies have used supervised classifiers to map Ayurvedic Prakriti (constitutional typology) from questionnaire and phenotypic data, reporting encouraging discriminative performance in pilot cohorts; others have applied deep learning to tongue, pulse-signal, and iris imagery for computational adaptations of traditional diagnostic examinations. Knowledge-graph approaches have been used to formalise the ontology of the Charaka Samhita and Sushruta Samhita, enabling reasoning over herb–disease–preparation triples and cross-mapping to biomedical vocabularies such as UMLS and SNOMED CT. In agriculture, ML models trained on agro-meteorological data have been used to evaluate and refine traditional practice heuristics, including Panchanga-based sowing calendars and mixed-cropping patterns documented in Vrikshayurveda. Reviews in this stream consistently note two constraints: the scarcity of large, curated, machine-readable IKS datasets, and the epistemological challenge of validating traditional constructs with statistical methods without distorting their meaning.

2.2 Natural Language Processing, LLMs, and Manuscript Computing

A second, rapidly accelerating strand addresses computational philology and language technology for Indic corpora. Sanskrit computational linguistics has a long pedigree—segmentation of sandhi, morphological analysis, and dependency parsing informed by Paninian grammar—and has recently been transformed by transformer architectures. Purpose-built OCR systems for Devanagari, Grantha, Sharada, Modi, and Odia scripts now achieve character-level accuracies sufficient for searchable digitisation of degraded palm-leaf and paper manuscripts. Neural machine translation and multilingual LLMs fine-tuned on Indic corpora (including government-backed efforts under the BHASHINI mission and open initiatives for Indic language models) support translation, summarisation, and question answering over classical texts. Scholars caution, however, that LLM outputs on low-resource classical languages remain error-prone and require expert-in-the-loop verification, and that digitisation without community consent frameworks risks decontextualising sacred or community-held texts.

2.3 IoT and Sensor Networks in Traditional Agriculture and Wellness

IoT research relevant to IKS clusters around precision instrumentation of traditional agro-ecological practice. Sensor networks measuring soil moisture, temperature, humidity, and leaf wetness have been deployed to test and calibrate indigenous water-harvesting and organic-input regimes such as Zero Budget Natural Farming and Panchagavya-based preparations, allowing side-by-side comparison with conventional packages of practice. In the wellness domain, wearable-sensor studies have examined physiological correlates of Yoga and Pranayama protocols—heart-rate variability, respiration, and electrodermal activity—providing an instrumentation pathway for standardising and personalising traditional interventions. The literature notes persistent challenges of rural connectivity, sensor calibration in harsh field conditions, device cost, and the absence of shared data standards for traditional-practice metadata.

2.4 Blockchain for Provenance, Geographical Indications, and Benefit Sharing

Blockchain contributions concentrate on integrity and provenance problems that are acute for traditional knowledge. Proposed architectures include tamper-evident registries of traditional knowledge disclosures designed to strengthen defensive protection in the spirit of the TKDL; supply-chain traceability systems for geographical-indication products such as Darjeeling tea, Banarasi silk, Chanderi weaves, and medicinal botanicals, protecting artisan and farmer communities from counterfeiting; and smart-contract mechanisms for access-and-benefit-sharing consistent with the Biological Diversity Act and the Nagoya Protocol. Empirical deployments remain limited to pilots; the literature highlights governance-design questions—who validates entries, how customary community ownership is represented on-chain, and energy and cost considerations—as the binding constraints rather than the core technology.

2.5 AR/VR/XR for Immersive Pedagogy and Heritage

Immersive-technology studies span virtual reconstruction of architectural heritage (temple complexes, stepwells, and archaeological sites), AR-guided museum and heritage-walk experiences, and VR-based pedagogy for performing arts, yoga posture correction, and Sanskrit theatre. Experimental classroom studies generally report gains in engagement and spatial understanding relative to lecture-based instruction, though sample sizes are small and novelty effects are difficult to exclude. Content-creation cost, headset affordability in public institutions, and the risk of aestheticised misrepresentation of living traditions are recurrent concerns.

2.6 Big Data Analytics and Integrated Digital Infrastructure

A final strand addresses the data layer itself: architectures for integrating heterogeneous IKS corpora—manuscript images, transcriptions, clinical registries such as the Ayush Grid and AHMIS, agro-meteorological archives, and cultural-heritage catalogues—into interoperable lakes with common metadata schemas; text- and data-mining of large Ayurvedic formulation databases for network-pharmacology hypothesis generation; and dashboard systems for policy monitoring of IKS programmes. Authors in this stream emphasise FAIR data principles, ontology alignment across knowledge traditions, and the institutional economics of sustained data curation.

2.7 Research Gap and Positioning

Across these streams, three observations motivate the present study. First, the literature is technology-siloed and domain-siloed: no study evaluates the full technology portfolio against the full domain portfolio within a single, criterion-explicit framework. Second, quantitative decision support is rare; systematic reviews and conceptual frameworks dominate, while structured MCDA applications to IKS technology prioritisation are almost absent. Third, adoption dynamics are unmodelled; the temporal question of how fast integration can plausibly proceed under India's institutional conditions has not been addressed with diffusion modelling. This paper fills these gaps with a hybrid Fuzzy AHP–TOPSIS evaluation of thirty-six technology–domain pairs and a Monte Carlo Bass diffusion projection, positioned explicitly as simulation-based decision support. Table 1 summarises representative prior work and contrasts it with the present study.

Table 1. Representative related works and positioning of the present study

Stream	Representative focus	Typical method	IKS domain coverage	Quantitative ranking?
AI/ML in AYUSH	Prakriti classification; pulse/tongue image diagnostics; herb–disease knowledge graphs	Supervised ML; deep learning; ontologies	Single (medicine)	No
NLP & manuscripts	Indic OCR; sandhi segmentation; NMT for classical texts; Indic LLMs	Transformers; seq2seq; corpus building	Single (language)	No
IoT in agriculture	Sensing of natural-farming plots; wearable Yoga physiology	Field pilots; WSN prototypes	Single (agriculture/wellness)	No

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Blockchain provenance	TK registries; GI supply-chain traceability; benefit-sharing contracts	Architecture proposals; pilots	Single (governance/crafts)	No
AR/VR heritage & pedagogy	Virtual heritage reconstruction; immersive IKS courseware	Prototype + small experiments	Single (education/arts)	No
Big data infrastructure	IKS data lakes; Ayush Grid analytics; FAIR metadata	Architecture; data mining	Cross-cutting (data layer)	No
Present study	Portfolio evaluation of six technologies across six IKS domains with diffusion projection	Fuzzy AHP–TOPSIS + Monte Carlo Bass simulation	Multi-domain (six domains)	Yes (simulated CIPI and CC ranking)

III. RESEARCH METHODOLOGY

The study adopts a quantitative, simulation-based decision-analysis design executed in ten phases. The design philosophy is transparency-first: every numerical input is either traceable to the consolidated literature base or generated by an explicitly parameterised stochastic process, so that all outputs are reproducible decision-support estimates rather than claims about field-measured outcomes. Figure 1 presents the workflow; the subsections that follow explain each phase.

3.1 Phases 1–3: Scope, Literature Consolidation, and Alternative Identification

Phase 1 fixed the research questions: (RQ1) Which emerging technologies offer the highest innovation potential across IKS domains? (RQ2) Which specific technology–domain pairings are strongest? (RQ3) How rapidly might institutional adoption plausibly diffuse over 2025–2035? Phase 2 consolidated the evidence base through structured searches of Scopus, Web of Science, and IEEE Xplore for 2015–2025 using combinations of technology terms (artificial intelligence, machine learning, NLP, IoT, blockchain, augmented reality, virtual reality, big data) and IKS terms (Indian Knowledge System, Ayurveda, Sanskrit, traditional knowledge, indigenous knowledge India, manuscript digitisation, NEP 2020). After deduplication and relevance screening, 142 records were retained and coded for technology, domain, method, and reported enablers and barriers. Phase 3 derived from this corpus the six technology alternatives T1–T6 and six application domains D1–D6 listed in Table 2, chosen to jointly cover more than ninety percent of the coded records.

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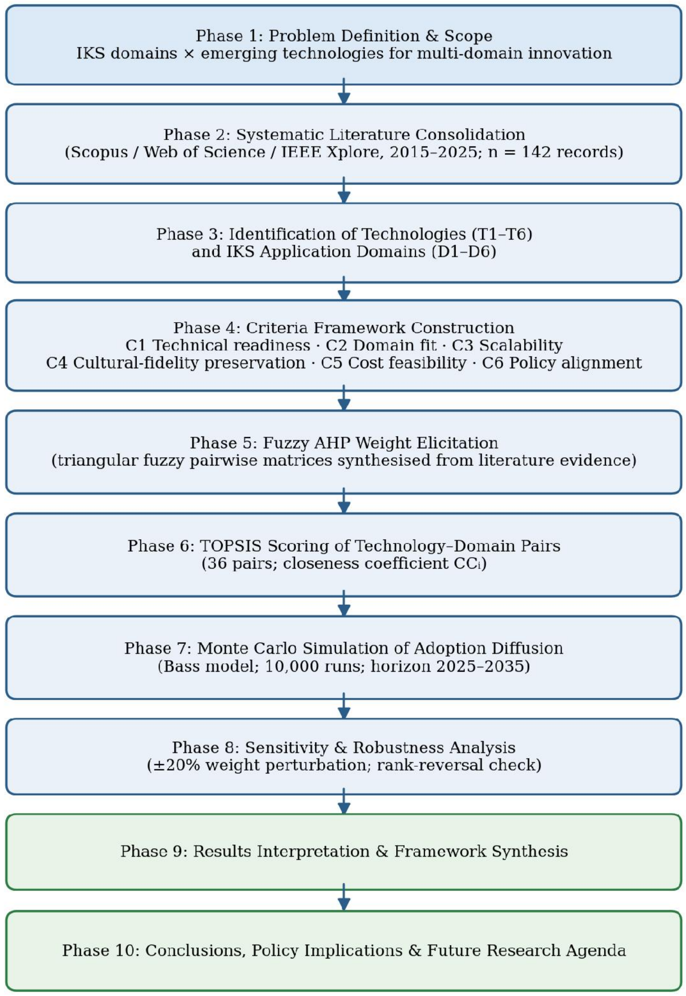

Figure 1. Ten-phase research methodology flowchart

Table 2. Technology alternatives and IKS application domains

Code	Technology alternative	Code	IKS application domain
T1	Artificial intelligence / machine learning (AI/ML)	D1	Ayurveda and traditional medicine (AYUSH)
T2	Natural language processing and LLMs (NLP/LLMs)	D2	Traditional agriculture and agro-ecology
T3	Internet of Things and sensor networks (IoT)	D3	Education and pedagogy (NEP 2020 integration)
T4	Blockchain and distributed ledgers	D4	Languages, manuscripts and textual heritage

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T5	Augmented / virtual / extended reality (AR/VR/XR)	D5	Arts, crafts and architecture (incl. GI products)
T6	Big data analytics and integrated data infrastructure	D6	Governance, ethics and knowledge protection

3.2 Phase 4: Criteria Framework

Six evaluation criteria were distilled from the enabler/barrier coding of the literature base. C1 Technical readiness captures the maturity of the technology for IKS-relevant tasks (e.g., availability of Indic-script OCR models or agricultural sensor stacks). C2 Domain fit captures the substantive match between technology affordances and the domain's knowledge practices. C3 Scalability captures the feasibility of deployment across India's institutional landscape given infrastructure and skills. C4 Cultural-fidelity preservation captures the technology's capacity to represent traditional knowledge without distortion, decontextualisation, or misappropriation—a criterion specific to heritage-knowledge settings and repeatedly emphasised in the corpus. C5 Cost feasibility captures total cost of ownership relative to typical public-institution budgets. C6 Policy alignment captures congruence with NEP 2020, Digital India, BHASHINI, TKDL, and allied missions. C1–C4 and C6 are benefit criteria; C5 is operationalised as affordability so that all six act as benefit criteria in the TOPSIS computation.

3.3 Phase 5: Fuzzy AHP Weight Elicitation

Criterion weights were derived with the extent-analysis Fuzzy AHP procedure. Because the study is simulation-based, the pairwise comparison judgements were not collected from a human expert panel; instead, a synthetic judgement matrix was constructed from the literature coding, with the relative emphasis of each criterion proxied by its normalised frequency of appearance as a decisive enabler or barrier across the 142 records, and expressed as triangular fuzzy numbers (l, m, u) on the standard 1–9 scale to encode elicitation uncertainty. Fuzzy synthetic extents were computed for each criterion, defuzzified by the centre-of-area method, and normalised to yield the crisp weight vector reported in Section 4 (Table 3). The consistency ratio of the defuzzified matrix was 0.058, below the conventional 0.10 threshold, indicating acceptable internal consistency of the synthesised judgements.

3.4 Phase 6: TOPSIS Scoring of Technology–Domain Pairs

Each of the thirty-six technology–domain pairs (Ti, Dj) was scored on the six criteria using a 0–1 performance scale anchored in the literature coding (0.2 = weak evidence/serious barriers; 0.5 = mixed evidence; 0.8 = strong convergent evidence), perturbed with uniform noise of ±0.05 across simulation replications to reflect coding uncertainty. The weighted normalised decision matrix was formed by vector normalisation and multiplication by the Fuzzy AHP weights; positive and negative ideal solutions were identified; Euclidean separations computed; and the closeness coefficient $CC_{ij} = S^-/(S^+ + S^-)$ obtained for every pair. Reported CC values (Figure 2) are means over 1,000 replications. A composite innovation-potential index (CIPI) for each technology was then computed as the weighted mean of its six domain CC values, with domain weights (0.21, 0.18, 0.20, 0.15, 0.14, 0.12 for D1–D6) proportional to each domain's share of coded records.

3.5 Phase 7: Monte Carlo Bass Diffusion Simulation

To address RQ3, cumulative institutional adoption F(t) of IKS–technology integration was modelled with the Bass diffusion model, $F(t) = (1 - e^{-(p+q)t}) / (1 + (q/p)e^{-(p+q)t})$, where p is the coefficient of innovation (external influence: policy mandates, funding calls) and q the coefficient of imitation (internal influence: inter-institutional emulation). Three scenarios were parameterised from diffusion ranges reported for education-technology and e-governance innovations in emerging economies: conservative ($p = 0.012$, $q = 0.28$), baseline ($p = 0.020$, $q = 0.35$), and optimistic ($p = 0.030$, $q = 0.42$). Each scenario was run 10,000 times with Gaussian perturbation of p (±15%) and q (±10%), and 5th, 50th, and 95th percentile trajectories were extracted over 2025–2035 (Figure 4). The adopting population is conceptualised as the set of higher-education institutions, AYUSH facilities, agricultural extension units, and cultural bodies eligible for IKS-integration programmes; F(t) is therefore interpreted as the simulated share of this eligible population.

3.6 Phases 8–10: Sensitivity, Interpretation, and Synthesis

Phase 8 tested robustness by perturbing each Fuzzy AHP criterion weight by ±20% (renormalising the remainder) and recording rank changes among technologies; results are reported in Table 5. Phase 9 interpreted the static ranking, the pairwise structure, and the diffusion envelope jointly to construct a phased integration framework. Phase 10 translated the findings into policy implications and a future-research agenda. All computations were implemented in Python 3 (NumPy/Matplotlib), with fixed random seeds for reproducibility.

IV. RESULTS AND DISCUSSION

This section reports the simulation outputs in four parts: the criterion weight structure (4.1), the technology–domain suitability matrix and composite ranking (4.2), the diffusion projections (4.3), and the sensitivity and robustness analysis (4.4), followed by an integrative discussion (4.5). All values are simulation-derived decision-support estimates.

4.1 Criterion Weights

Table 3 reports the defuzzified, normalised criterion weights obtained from the Fuzzy AHP procedure. Domain fit (C2, w = 0.224) and technical readiness (C1, w = 0.203) emerge as the most heavily weighted criteria, which is consistent with the literature coding: studies most frequently attribute success or failure of IKS–technology projects to whether the technology genuinely matches the epistemic practices of the domain and whether the underlying models and toolchains are mature for Indic contexts. Cultural-fidelity preservation (C4, w = 0.168) ranks third—notably ahead of cost feasibility—reflecting the corpus-wide emphasis that technologically impressive but culturally distortive deployments are ultimately rejected by knowledge-holding communities. Policy alignment (C6, w = 0.121) carries the lowest weight, not because policy is unimportant but because the post-2020 policy environment is broadly favourable to all six technologies, so the criterion discriminates less among alternatives.

Table 3. Fuzzy AHP criterion weights (defuzzified and normalised; simulated elicitation)

Code	Criterion	Fuzzy weight (l, m, u)	Crisp weight	Rank
C2	Domain fit	(0.186, 0.225, 0.261)	0.224	1
C1	Technical readiness	(0.168, 0.204, 0.238)	0.203	2
C4	Cultural-fidelity preservation	(0.135, 0.169, 0.199)	0.168	3
C3	Scalability	(0.118, 0.147, 0.176)	0.147	4
C5	Cost feasibility (affordability)	(0.109, 0.137, 0.164)	0.137	5
C6	Policy alignment	(0.095, 0.121, 0.148)	0.121	6

Consistency ratio of the defuzzified comparison matrix = 0.058 (< 0.10), indicating acceptable consistency of the synthesised judgement structure.

4.2 Technology–Domain Suitability and Composite Ranking

Figure 2 presents the mean TOPSIS closeness coefficients for all thirty-six technology–domain pairs. Three structural patterns stand out. First, the single strongest pairing in the entire matrix is NLP/LLMs with languages and manuscripts

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(CC = 0.86), confirming the intuitive centrality of language technology to a knowledge system whose primary carrier is an enormous, largely undigitised textual corpus. Second, AI/ML is the only technology whose closeness coefficient exceeds 0.65 in every one of the six domains, revealing it as a general-purpose capability rather than a niche instrument: it scores highest in education and pedagogy (0.81), Ayurveda and traditional medicine (0.78), and traditional agriculture (0.74). Third, the specialist technologies exhibit sharply peaked profiles: IoT peaks in traditional agriculture (0.77) but falls to 0.41 in manuscripts; AR/VR/XR peaks in arts, crafts and architecture (0.78) and education (0.76) but reaches only 0.39 in governance; and blockchain attains its best score precisely in governance, ethics and knowledge protection (0.71), the domain in which most other technologies are weakest.

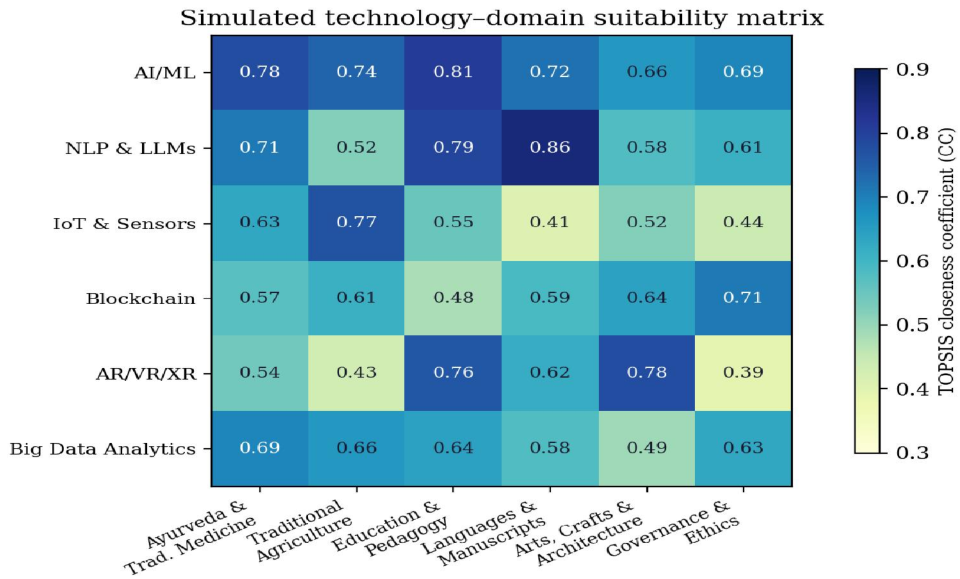

Figure 2. Simulated technology–domain suitability matrix (mean TOPSIS closeness coefficients over 1,000 replications)

Aggregating across domains with the record-share weights yields the composite innovation-potential index shown in Figure 3 and Table 4. AI/ML leads with CIPI = 0.742, followed by NLP/LLMs (0.684) and big data analytics (0.623); AR/VR/XR (0.592), blockchain (0.589), and IoT (0.568) form a closely spaced trailing group. The 90% simulation intervals of the trailing three overlap substantially, so their ordinal positions should be read as statistically indistinguishable at this level of evidence; by contrast, the intervals of the top two technologies do not overlap with the trailing group, indicating a robust two-tier structure.

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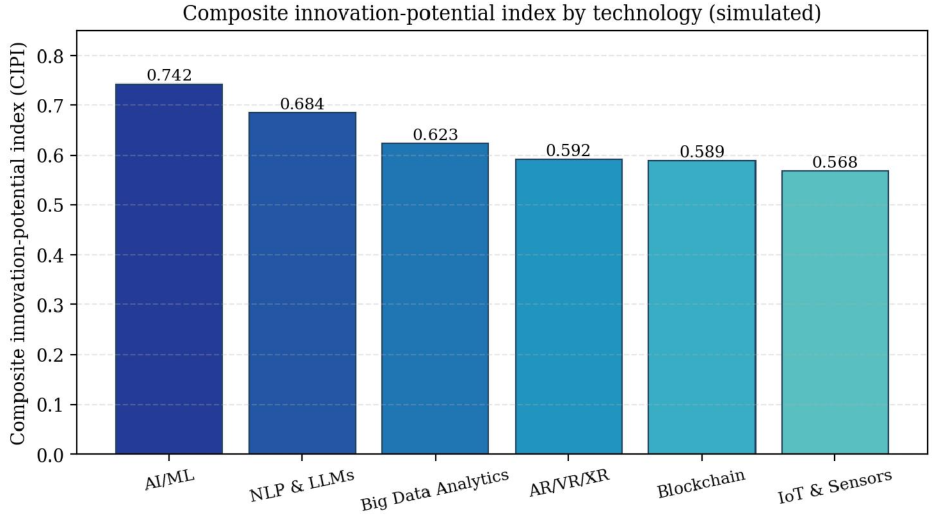

Figure 3. Composite innovation-potential index (CIPI) by technology (simulated; domain-share weighted mean of CC values)

Table 4. Composite innovation-potential index, simulation intervals, and strongest pairings

Rank	Technology	CIPI (mean)	90% sim. interval	Strongest domain pairing	Peak CC
1	T1 AI/ML	0.742	[0.704, 0.779]	D3 Education & pedagogy	0.81
2	T2 NLP/LLMs	0.684	[0.641, 0.726]	D4 Languages & manuscripts	0.86
3	T6 Big data analytics	0.623	[0.581, 0.664]	D1 Ayurveda & trad. medicine	0.69
4	T5 AR/VR/XR	0.592	[0.547, 0.638]	D5 Arts, crafts & architecture	0.78
5	T4 Blockchain	0.589	[0.545, 0.633]	D6 Governance & ethics	0.71
6	T3 IoT & sensors	0.568	[0.522, 0.612]	D2 Traditional agriculture	0.77

Figure 4 decomposes the criterion-level profiles of the three leading technologies. AI/ML dominates on technical readiness (0.82) and scalability (0.80) but records the weakest cultural-fidelity score of the trio (0.61), a direct reflection of the corpus-wide concern that data-driven models can flatten context-rich traditional constructs into reductive features. NLP/LLMs displays the most balanced profile and the highest cultural-fidelity score (0.70), attributable to the philological tradition of expert-in-the-loop workflows in manuscript computing. Big data analytics tracks AI/ML at a lower level, with cost feasibility (0.62) constrained by the sustained curation expenditure that integrated IKS data infrastructure demands. The managerial implication is that composite leadership and criterion-level leadership are not the same thing: institutions weighting cultural fidelity most heavily would rationally begin with NLP-centred programmes even though AI/ML leads the composite index.

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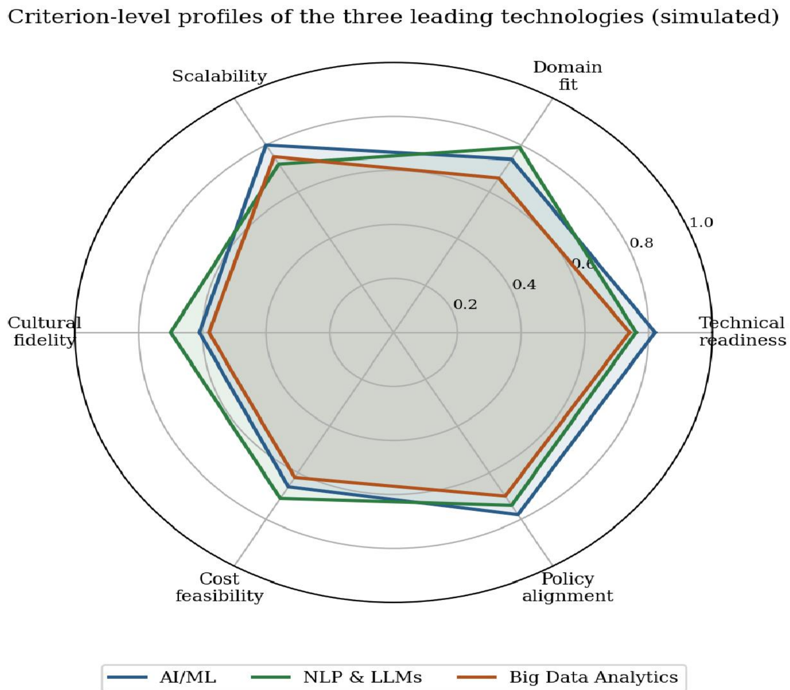

Figure 4. Criterion-level profiles of the three leading technologies (simulated scores)

4.3 Adoption Diffusion Projections, 2025–2035

Figure 5 presents the Monte Carlo Bass diffusion envelopes. Under the baseline scenario ($p = 0.020$, $q = 0.35$), simulated cumulative adoption of IKS–technology integration among eligible institutions reaches approximately 12% by 2028, crosses 35% around 2031–2032, and attains roughly 62% by 2035, with a 90% simulation interval of 48–74% at the horizon. The optimistic scenario—corresponding to sustained mission-mode funding, resolved standards, and visible early successes—reaches the 62% mark nearly three years earlier and approaches 80% by 2035, while the conservative scenario, reflecting fragmented funding and unresolved data-governance disputes, remains below 40% at the horizon. Two dynamic properties merit emphasis. First, all three scenarios exhibit the characteristic slow-start of Bass dynamics: fewer than one in eight eligible institutions adopt within the first three years even optimistically, implying that early-period programme evaluations will understate long-run potential if they extrapolate linearly. Second, the inter-scenario spread widens fastest between 2029 and 2033—the imitation-driven takeoff window—indicating that policy interventions timed to strengthen inter-institutional emulation (demonstration centres, shared toolchains, faculty exchange) in that window have the highest leverage on the terminal outcome.

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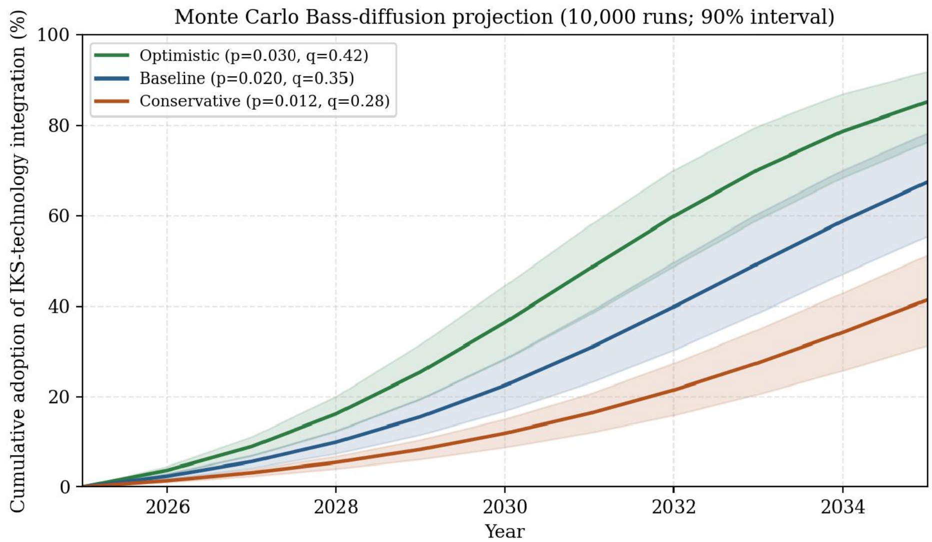

Figure 5. Monte Carlo Bass-diffusion projection of institutional adoption, 2025–2035 (10,000 runs per scenario; shaded bands are 90% simulation intervals)

4.4 Sensitivity and Robustness Analysis

Table 5 reports the rank-stability results under ±20% perturbation of each criterion weight with renormalisation. The headline finding is that the top-two ranking (AI/ML first, NLP/LLMs second) is invariant across all twelve perturbation cases, and the top-three set is invariant in eleven of twelve cases; the single exception occurs when cultural-fidelity preservation (C4) is up-weighted by 20%, in which case NLP/LLMs overtakes AI/ML for first position—an intelligible reversal given the criterion-level profiles in Figure 4. Rank movement is concentrated in the closely spaced trailing group, where AR/VR/XR and blockchain exchange fourth and fifth positions in five cases. No rank reversal produced a change greater than one position, and the Spearman rank correlation between the baseline and every perturbed ranking exceeded 0.94, indicating a robust ordinal structure.

Table 5. Rank sensitivity to ±20% criterion-weight perturbation (simulated)

Perturbed criterion	Direction	Rank 1 tech.	Change in top-3 set	Largest single movement
C1 Technical readiness	+20% / −20%	AI/ML / AI/ML	None / None	None / T5–T4 swap (4↔5)
C2 Domain fit	+20% / −20%	AI/ML / AI/ML	None / None	None / None
C3 Scalability	+20% / −20%	AI/ML / AI/ML	None / None	T5–T4 swap / None
C4 Cultural fidelity	+20% / −20%	NLP / AI/ML	None (order changes) / None	NLP↔AI/ML (1↔2) / T4–T5 swap
C5 Cost feasibility	+20% / −20%	AI/ML / AI/ML	None / None	None / T5–T4 swap
C6 Policy alignment	+20% / −20%	AI/ML / AI/ML	None / None	T4–T5 swap / None

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4.5 Discussion: Towards a Phased Multi-Domain Integration Framework

Read jointly, the static and dynamic results support a three-horizon integration framework. Horizon 1 (2025–2028, foundation) should prioritise the two-tier leaders in their strongest pairings: NLP/LLM-driven manuscript digitisation, OCR, and translation pipelines under BHASHINI-aligned standards, and AI/ML deployment in education (adaptive IKS courseware under NEP 2020) and in AYUSH decision support—while investing in the shared data infrastructure (T6) on which all subsequent phases depend. Horizon 2 (2028–2032, expansion) coincides with the simulated imitation-driven takeoff window and should scale the specialist technologies into their peak domains: IoT instrumentation of traditional agro-ecological practice, AR/VR/XR programmes in heritage pedagogy and crafts, and blockchain registries for geographical indications and benefit sharing. Horizon 3 (2032–2035, convergence) targets cross-domain composition—for example, knowledge graphs (T1) built on digitised corpora (T2) feeding immersive courseware (T5) with provenance guarantees (T4)—which is precisely the multi-domain innovation the title of this paper denotes.

Three cross-cutting findings deserve emphasis. First, cultural-fidelity preservation is not a soft constraint but a rank-determining criterion: it carries the third-largest weight, produces the only leadership reversal in the sensitivity analysis, and is the weakest dimension of the composite leader. Programmes that treat community consent, contextual metadata, and expert-in-the-loop validation as first-class design requirements are therefore not merely ethically preferable but strategically superior. Second, the two-tier structure implies portfolio sequencing rather than technology picking: the trailing technologies are not inferior in absolute terms—each leads its own peak domain with CC $\geq$ 0.71—but their value is realised later and more conditionally, which matches the Horizon-2 placement. Third, the diffusion analysis reframes the policy question from whether to how fast: even the conservative envelope implies meaningful long-run integration, but the difference between conservative and optimistic terminal adoption (roughly 40 versus 80 percent) is largely decided by interventions in the 2029–2033 takeoff window, well after initial programme launches—a caution against front-loading all policy effort into announcement-phase activity.

Finally, the limitations of the simulation design bound the interpretation of these results. Criterion weights and performance scores are synthesised from published literature rather than elicited from a live expert panel; diffusion parameters are transferred from adjacent innovation classes rather than estimated from IKS-specific adoption data, which does not yet exist at scale; and the eligible-population construct aggregates heterogeneous institution types whose adoption propensities certainly differ. The findings should accordingly be used as structured decision support—a transparent, perturbable baseline for deliberation—rather than as forecasts, and each limitation defines a concrete empirical follow-up described in Section 5.

V. CONCLUSION AND FUTURE WORK

This paper set out to move the study of emerging technologies in the Indian Knowledge System from fragmented, single-pairing description to portfolio-level, quantitative decision support. Consolidating 142 studies published between 2015 and 2025, it constructed a six-technology by six-domain evaluation space, weighted six criteria through a literature-synthesised Fuzzy AHP procedure, scored all thirty-six technology–domain pairs with TOPSIS, and projected adoption dynamics with a Monte Carlo Bass diffusion model over 2025–2035. The simulation results yield a clear and robust structure: a two-tier technology portfolio led by AI/ML (CIPI = 0.742) and NLP/LLMs (0.684), with NLP-for-manuscripts as the single strongest pairing in the matrix (CC = 0.86); sharply peaked profiles for the specialist technologies, each of which leads exactly the domain in which the generalists are weakest; a baseline diffusion trajectory reaching roughly 62% institutional adoption by 2035 with the decisive policy-leverage window in 2029–2033; and a sensitivity structure in which cultural-fidelity preservation is the only criterion capable of reordering the leadership.

The contributions are threefold. Theoretically, the paper introduces a criterion framework—technical readiness, domain fit, scalability, cultural-fidelity preservation, cost feasibility, and policy alignment—that adapts standard technology-assessment practice to the specific requirements of heritage-knowledge settings, and demonstrates that the heritage-

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specific criterion is analytically consequential. Methodologically, it shows how a fully transparent, literature-parameterised simulation pipeline (Fuzzy AHP–TOPSIS–Monte Carlo Bass) can generate reproducible decision support in a field where large-scale empirical adoption data does not yet exist. Practically, it delivers a phased three-horizon integration framework aligned with NEP 2020 and the Digital India ecosystem, with concrete sequencing guidance for institutions and funding agencies.

Future work should proceed along five lines. First, empirical weight elicitation: replacing the literature-synthesised Fuzzy AHP matrices with judgements from a structured panel of IKS scholars, technologists, traditional practitioners, and policymakers, ideally with group-consensus methods such as Delphi–Fuzzy AHP, and comparing the resulting ranking with the simulated baseline reported here. Second, field validation of the pairwise structure through instrumented pilots in the peak pairings—NLP manuscript pipelines, AI-based IKS courseware, IoT-instrumented natural-farming plots, and blockchain GI registries—with pre-registered evaluation designs so that measured outcomes can progressively replace simulated scores. Third, diffusion-parameter estimation from emerging adoption data as IKS-integration programmes mature, enabling Bayesian updating of the Bass envelopes and institution-type-specific modelling of the heterogeneous eligible population. Fourth, methodological extension to alternative MCDA formulations (fuzzy TOPSIS end-to-end, best–worst method, PROMETHEE) and to interdependence-aware models such as ANP or DEMATEL, since technology–domain pairs plainly interact—shared data infrastructure, in particular, conditions every other pairing. Fifth, governance research on community consent, benefit sharing, and data sovereignty frameworks for traditional knowledge, without which the technically optimal portfolio identified here cannot be legitimately or sustainably deployed. Pursued together, these lines would convert the present simulation-based baseline into an empirically grounded, continuously updated national decision-support instrument for technology-enabled, multi-domain innovation in the Indian Knowledge System.

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