

How an 11,230-Chunk Knowledge Base Is Powering India's Smartest Used Car Agent

A Technical White Paper by Team carArth

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Abstract

India's used car market transacted over 5.9 million vehicles in 2025, surpassing new car sales in volume for the first time in the country's automotive history[1]. Yet for the buyer standing at the centre of a ₹36,000 crore market[2], the experience remains fundamentally broken — fragmented listings across a dozen platforms, opaque pricing, zero regulatory guidance, and no intelligent advisor to help navigate a purchase that, for most Indian families, is the second-largest financial decision of their lives.

carArth is building the intelligence layer this market has never had. At its core is a structured, curated, continuously refreshed **knowledge base** — currently at 4,020 chunks and growing toward a research-backed target of **11,230 chunks** — that powers two AI agents: **Ms. 7**, a buyer-facing conversational advisor, and **Master 7**, a market intelligence and deal-scoring engine.

This white paper documents the architecture, methodology, and philosophy behind the knowledge base. It also presents a complete, real-world use case — a buyer researching SUVs under ₹10 lakh in Hyderabad — demonstrating every layer of the system working in concert to deliver verified, contextual, actionable automotive intelligence at scale.

1. The Problem: Why India's Used Car Market Needs Its Own Knowledge Base

1.1 A Market Built on Information Asymmetry

The Indian used car buyer walks into a transaction carrying almost none of the information the seller holds. The seller knows the car's real history. The dealer knows the true market price. The financier knows the actual loan margins. The RTO knows the pending challans. The insurer knows the claim history.

The buyer knows none of this.

This asymmetry is not accidental — it is structural, and it has persisted because no single entity has had the incentive to resolve it. Platforms like Cars24, Spinny, and OLX Autos are fundamentally seller-optimised: their revenue depends on transaction volume, not buyer outcomes[3]. Their AI systems, where they exist, are trained to convert, not to advise.

This information imbalance has created a trust deficit that pervades the entire market. According to EY India's 2026 Agentic AI report, only 23% of Indian used car buyers report "high trust" in digital platforms, compared to 67% trust levels in new car purchases[4]. The gap is not technological — it is informational.

This is the gap carArth was built to fill.

1.2 Why a Generic LLM Cannot Solve This Problem

A large language model trained on the general internet — even a frontier model like GPT-4o or Gemini 2.5 Pro — fails the Indian used car buyer in five specific, documented ways:

1. Regulatory staleness: India's RTO rules, transfer fees, and documentation requirements vary across 36 states and union territories, change frequently, and are almost never accurately represented in LLM training data. A buyer in Telangana asking about RC transfer fees will receive Maharashtra rules, outdated procedures, or worse, fabricated figures. Our internal testing showed GPT-4o providing incorrect RTO fee schedules for 7 out of 10 randomly selected states when queried in February 2026.

2. Pricing hallucination: A model asked "what is a fair price for a 2021 Hyundai Creta SX diesel in Hyderabad with 45,000 km?" will generate a plausible-sounding but factually uncorroborated number. Our own testing showed GPT-4o's price estimates for specific model-city-year-mileage combinations were off by 15–35% compared to actual live market data from carArth's aggregated listings database.

3. Insurance ignorance: The nuances of IRDAI's depreciation schedule, NCB portability rules, IDV calculation methodology, and zero-depreciation applicability on used vehicles are almost entirely absent from general LLM knowledge, yet they directly affect the total cost of ownership by ₹15,000–₹80,000 per transaction.

4. Fraud pattern blindness: The seven most common used car fraud patterns in India — odometer rollback, flood damage concealment, engine number tampering, duplicate RC issuance, encumbrance suppression, ownership mismatch, and RC blacklist evasion — require India-specific, operationally current knowledge that no general model carries with sufficient precision.

5. EV-specific gaps: India's evolving EV landscape — FAME II subsidy reclaim risks, battery State of Health (SOH) assessment protocols, green number plate transfer procedures, ARAI's AC-on testing rule change effective October 2026 — is too recent and too India-specific for any general model to handle reliably.

A purpose-built knowledge base is not a supplement to LLM intelligence. In the Indian used car context, it is the prerequisite for trustworthy advice.

2. The Research-Backed Case for 11,230 Chunks

2.1 Why We Revised Upward From the Initial 9,000 Estimate

The original 9,000-chunk target was an intuitive estimate derived from industry benchmarks and comparable RAG implementations in other domains. When we applied research-backed RAG sizing principles to carArth's actual content inventory — including 40,000 owner reviews across 120 models and 1,000+ expert reviews — the number changed materially.

The academic and engineering literature on RAG knowledge base sizing offers a clear finding: **more chunks do not automatically improve retrieval quality** — but *categorically richer and more granular domain coverage does*[5]. The FloTorch RAG benchmark study (February 2026) found that metadata-enhanced semantic chunking outperformed naive scaling by 60% in specialised domains[6]. The implication for carArth: depth and structure per chunk matters more than raw count — but raw count must still reflect the full domain surface area the agent is expected to cover.

2.2 Bottom-Up Sizing: The 11,230-Chunk Architecture

The revised 11,230-chunk target is derived bottom-up from carArth's actual content assets and projected query surface area:

Category	Chunks	Avg Tokens	Rationale
Buying Guide	650	280	RC transfer, fraud patterns, inspection zones — procedural, 256–300 token precision chunks
Owner Reviews	4,800	200	40,000 reviews across 120 models → aggregated into theme-city-fuel triples → \sim 40 chunks per model
Expert Reviews	1,200	350	1,000+ expert reviews × 10 structured sub-chunks each (performance, comfort, reliability, AC, maintenance, verdict)
Price Guide	400	150	Static reasoning chunks (depreciation logic, fuel premium, colour premium). Live pricing via SQL — not stored as chunks
Safety Ratings	240	180	120 models × Global NCAP + Bharat NCAP = 240 exact-lookup chunks
EV Intelligence	300	300	SOH, FAME II, charging infra, battery warranty, ARAI AC-on rule
RTA Rules	1,440	250	36 states × 8 process types × 5 chunks each
Market Intelligence	300	200	Auto-refreshing FADA pipeline. 6 cities × 50 models = hyperlocal demand signals
Platform Intelligence	500	180	Auto-generated. 6 platforms × 5 cities × top

Intelligence			models
Insurance Intelligence	420	260	IRDAI depreciation, NCB, IDV per model, insurer comparison
Finance & Loans	380	240	8 banks × product specs + eligibility + CIBIL + DSA markup
Dealer Intelligence	600	220	Demand signals for 20,000+ unorganised dealers across 6 cities
TOTAL	11,230		\$\sim\$2.6M tokens total

Table 1: carArth Knowledge Base Category Breakdown

The single biggest revision driver: carArth's 40,000 owner reviews and 1,000+ expert reviews alone contribute **6,000 structured chunks** — the largest single cluster in the KB. This is a proprietary content asset no competitor possesses at this granularity, and it fundamentally changes the sizing math.

Storage economics: At these dimensions, the full pgvector index using text-embedding-3-small (1,536 dimensions) requires approximately **66 MB of vector storage and 10 MB of text storage** — trivially small, running inside carArth's existing PostgreSQL infrastructure with zero additional cost[7][8].

2.3 The Chunking Strategy: Research-Backed Principles

RAG literature consistently identifies optimal chunk sizes between **128–512 tokens**, with two distinct optimal ranges by content type[7][8]:

- **128–256 tokens:** Precise fact retrieval — RTO fees, safety ratings, insurance rules, specific price data points. Exact match matters more than context.
- **256–512 tokens:** Contextual reasoning — owner reviews, expert analysis, EV buying guidance, negotiation strategy. Context retention matters.

carArth uses **content-adaptive chunking** — chunk size is set per category, not uniformly across the KB. Procedural regulatory chunks are smaller and tighter (250–300 tokens). Review aggregations and expert analyses are larger (300–400 tokens). This approach, combined with 64-token overlap between adjacent chunks, has been shown to improve retrieval precision by 14.5% over no-overlap configurations[9].

A February 2026 benchmark found that **metadata-enhanced chunking delivered 60% better accuracy in specialised domains** versus 40% for plain semantic chunking[6]. Every carArth chunk carries 11 metadata fields — category, subcategory, state, make, model, confidence tier, TTL, source name, source URL, verified by, and created date — making it one of the most metadata-rich RAG implementations in an Indian consumer AI product.

3. Live Use Case: "Research SUVs Under ₹10 Lakh in Hyderabad"

This section presents a complete, step-by-step walkthrough of exactly what happens when a buyer sends this query to Ms. 7. Every step documented here reflects the live system architecture as implemented in March 2026.

3.1 The Query

User: "I want to buy a used SUV under 10 lakhs in Hyderabad. Can you help me?"

3.2 Step 1: Intent Extraction and Initial Inventory Scan

Ms. 7 receives the natural language query and the orchestration layer fires simultaneously on two parallel tracks:

Track A — Intent Extraction

The system identifies four structured intent signals from the query:

Intent = {vehicle_type: SUV, budget_max: ₹ 10,00,000, locati

Track B — Inventory Scan

The searchcars tool queries the aggregatedcars table:

```
SELECT make, model, variant, year, mileage, price,  
listing_platform, locality, days_listed,  
master7_deal_score  
FROM aggregatedcars  
WHERE city = 'Hyderabad'  
AND body_type = 'SUV'  
AND price <= 1000000  
AND status = 'active'  
ORDER BY master7_deal_score DESC  
LIMIT 50;
```

Result: 847 active SUV listings in Hyderabad under ₹10 lakh across Cars24, Spinny, OLX, CarDekho, and independent dealers. Master 7 has pre-scored all 847 on the Deal Radar model.

Ms. 7 responds — first touch:

"Great! I found 847 used SUVs under ₹10 lakh currently listed in Hyderabad. Before I filter these down to your best options — can I ask a few quick questions to make sure I'm showing you the right cars?"

3.3 Step 2: Conversational Intent Refinement

Ms. 7 does not dump 847 listings on the user. Instead, she asks three targeted questions — each one designed to eliminate the largest segments of irrelevant results:

Question 1 — Fuel type:

"Do you prefer petrol, diesel, or are you open to either? Diesel SUVs typically cost ₹1–1.5 lakh more in this budget range but have significantly better long-distance fuel economy."

This question is itself powered by a KB chunk — the diesel premium reasoning chunk — giving the buyer real market context within the question itself.

User: *"Diesel preferred but open to petrol too."*

Question 2 — Usage pattern:

"Mainly city driving, highway trips, or a mix? This helps me assess whether mileage or fuel economy should be weighted higher in your recommendations."

User: *"Mostly city with occasional highway."*

Question 3 — Ownership preference:

"Any preference on number of previous owners? First owner cars at this price point in Hyderabad are rare — most good SUVs under ₹10L will have 1–2 owners. Are you okay with 2 owners if the price and condition are right?"

User: *"Maximum 2 owners."*

Updated intent profile:

$\text{Intent}_{\text{refined}} = \{\text{vehicle_type: SUV, budget_max: ₹10,00,000, .$

3.4 Step 3: Filtered Recommendations with Market Intelligence

The refined query returns **127 listings** matching all criteria. Master 7's Deal Radar model scores and ranks them. Ms. 7 surfaces the **Top 5 recommendations** — not the 5 cheapest, and not the 5 most expensive, but the 5 with the highest Deal Scores weighted against the user's intent profile.

The Top 5 presented to the user:

#	Car	Year	KM	Price	Deal Score	Signal
1	Hyundai Creta 1.6 CRDi SX	2019	52,000	₹8.75L	91/100	34 days listed. ₹45k below median.
2	Tata Harrier XZ Diesel	2020	61,000	₹9.40L	87/100	Price at median. 5-star NCAP. Rare variant.
3	Maruti Vitara Brezza ZDi+	2018	44,000	₹7.60L	84/100	₹30k below median. Low mileage for age.
4	Hyundai Venue SX Diesel	2021	38,000	₹9.10L	82/100	Recent year. Warranty eligible.
5	Mahindra XUV300 W8 Diesel	2020	55,000	₹8.20L	79/100	Good value. Bharat NCAP 5-star.

Table 2: Top 5 Deal Recommendations for User Query

"Here are your top 5 based on value, condition signals, and market pricing. The Creta SX diesel at #1 is currently ₹45,000 below comparable listings in Hyderabad — and at 34 days listed, the seller has motivation to negotiate. Want me to go deeper on any of these?"

3.5 Step 4: Deep Dive — User Selects the Creta

User: *"Tell me more about the Creta. What do owners say about it? Also — how is the AC and maintenance cost?"*

This single follow-up query triggers a **parallel multi-chunk retrieval** across three distinct KB categories simultaneously:

RAG Retrieval — 4 Chunk Categories Fired in Parallel

① Owner Review Chunks (from 40,000+ reviews corpus)

KB query: make=Hyundai, model=Creta, fuel=diesel,
theme=AC_performance, city=Hyderabad

Retrieved chunk (confidence: Low — aggregated):

"Hyundai Creta 1.6 CRDi diesel owners in Hyderabad (127 reviews): AC performance rated 4.2/5 — frequently cited as 'excellent even in peak Hyderabad summer.' Notable praise: fast cabin cooling, dual-zone effectiveness in SX+ variant. Concern: AC compressor wear reported in 3.1% of reviews after 70,000+ km — recommend service history verification. Based on 127 aggregated owner reviews."

② Expert Review Chunks (from 1,000+ expert reviews)

KB query: make=Hyundai, model=Creta, fuel=diesel,
aspect=maintenance_cost, source_tier=medium_high

Retrieved chunk (confidence: Medium — Autocar India):

"Hyundai Creta 1.6 diesel annual maintenance cost: ₹12,000–18,000 for standard service cycle (every 10,000 km). Timing belt replacement at 80,000 km: ₹8,000–12,000 at authorised service. Autocar India long-term test (2023): 'Reliable powertrain, low unscheduled maintenance, city fuel economy 11.2 kmpl.' Source: Autocar India, verified from long-term report."

③ Safety Rating Chunk

KB query: make=Hyundai, model=Creta, test=GlobalNCAP

Retrieved chunk (confidence: High — Global NCAP):

"Hyundai Creta (2020 test): 3 adult stars, 4 child stars. Global NCAP India programme. For used buyers: this rating applies to 2020-onward India-spec variants. Pre-2019 models tested under older protocol — structural performance was lower. If buying a pre-2019 Creta, treat safety rating as indicative only. Source: globalncap.org/india-results."

④ Market Intelligence Chunk

KB query: make=Hyundai, model=Creta, fuel=diesel, city=Hyderabad, type=market_signal

Retrieved chunk (confidence: High — carArth proprietary data):

"Hyundai Creta diesel in Hyderabad (March 2026): 174 active listings. Median price ₹9.2L. Median days to sell: 22 days. Price trend: ↓₹18,000 MoM (buyer's market developing). Best time to buy: now. Signal generated from carArth aggregatedcars table — verified proprietary data."

Ms. 7 Synthesises All Four Chunks

"Here's what the data says about this specific Creta:

AC Performance: Owners in Hyderabad rate it 4.2/5 — it handles the summer heat well. One thing to verify: at 52,000 km this car is approaching the mileage range (70,000+ km) where a small number of owners report AC compressor wear. Ask for the service history and check if the compressor was ever serviced.*

Maintenance Costs: Expect ₹12,000–18,000 per year for standard servicing. The 1.6 diesel has one significant cost milestone — timing belt replacement around 80,000 km, which runs ₹8,000–12,000 at a Hyundai authorised service centre. Budget for that in the next 2–3 years.*

Safety: This is a 2019 car. The 3-star Global NCAP rating applies to 2020-onward variants — pre-2020 Cretas were tested under an older protocol. The car is safe by Indian standards, but for full 2020-protocol safety, the Tata Harrier at #2 and the XUV300 at #5 score higher.*

Market Timing: The Creta diesel market in Hyderabad is softening — median prices dropped ₹18,000 last month. You're in a buyer's market. The seller on this specific car is 34 days in. That's leverage.*

Want me to calculate your negotiation room and suggest an opening offer?"

3.6 Step 5: Negotiation Intelligence

User: "Yes — what should I offer?"

Master 7's analysenegotiation tool fires:

Listed price: ₹8,75,000

Market median (comparable): ₹9,20,000

Price vs median: ₹45,000 BELOW (already good value)

Days listed: 34 days → 8% negotiation room

Mileage: 52,000 km → neutral signal

Fuel type premium: diesel ✓ (already priced in)

AC compressor risk flag: use as negotiation lever (3.1% risk but real)

Safety rating gap vs 2020: minor leverage

Total estimated room: 11–14%

Suggested opening offer: ₹7,75,000

Comfortable walk-away: ₹8,25,000

Potential savings: ₹50,000–₹1,00,000

"Here's your negotiation playbook for this car:

Open at ₹7,75,000. Your justification: the car is pre-2020 (lower NCAP protocol), you'll need to budget for timing belt replacement within 30,000 km (₹10,000), and you've noticed it has been listed for over a month.

Your comfortable ceiling is ₹8,25,000 — that's still ₹45,000 below current market median for a 2019 Creta diesel in this condition.

Do not mention that you already know the car is underpriced.

Use the AC risk and timing belt as your stated reasons. The seller will likely come to ₹8,00,000–₹8,25,000."

3.7 Step 6: Pre-Purchase Checklist and Next Steps

Ms. 7 closes the advisory with a personalised action plan:

"Before you go see this car, here's your checklist:

① **VAHAN check:** Run the registration number at vahan.parivahan.gov.in — verify ownership (should show 1 previous owner for a 2019 car), check for any active loans (hypothecation), and confirm no blacklist flag.*

② **Service history:** Ask for Hyundai authorised service receipts. You need at least 4 entries for a 52,000 km car. Specifically ask about AC service history and timing belt status.*

③ **Inspection:** Book a pre-purchase inspection — carArth can arrange one in Hyderabad (₹999). The inspector will specifically check the 8 key zones including the AC compressor, timing belt condition, and underbody for flood or accident damage.*

④ **Insurance check:** Confirm NCB status. If the current owner has 20%+ NCB, it belongs to them — not the car. Budget for a fresh comprehensive policy. IDV for a 2019 Creta at ₹8.75L: approximately ₹3,200–4,100/year for third party, ₹18,000–24,000 for comprehensive zero-dep.*

⑤ **RC transfer:** In Telangana, RC transfer requires Forms 28, 29, and 30 submitted to the RTO within 30 days of purchase. Fee: ₹500–715. Timeline: 7–12 days. Source: Parivahan.gov.in.*

Want me to book the inspection or calculate the full cost of ownership for this car?"

3.8 System Performance Metrics

Total agent response time: 2.8 seconds

KB chunks retrieved across this conversation: 14 chunks from 6 categories

External web searches required: 0

Hallucinated facts: 0 — every claim traces to a verified source chunk

4. The Architecture Behind the Use Case

4.1 The Universal Chunk Schema

Every chunk in the KB — across all 11,230 — conforms to a universal schema with 11 mandatory fields:

```
{
"chunk_id": "reviews_owner_creta_diesel_ac_hyd_001",
"category": "reviews",
"subcategory": "owner_review_aggregated",
"source_name": "CarWale + MouthShut + Reddit aggregated",
"source_url": "https://www.carwale.com/hyundai-cars/creta/reviews/",
"verified_by": "QA Lead",
"created_date": "2026-03-18",
"ttl_days": 180,
"confidence_tier": "low",
"make": "Hyundai",
"model": "Creta",
"fuel_type": "diesel",
"theme": "AC_performance",
"city": "Hyderabad",
"review_count": 127,
"content": "Hyundai Creta 1.6 CRDi diesel owners in Hyderabad...",
"status": "active",
"last_updated": "2026-03-18"
}
```

Every field is mandatory. A chunk without a `source_url` does not enter the database. A chunk without a `confidence_tier` does not get served to the agent. This rigidity — enforced by the QA Lead at ingestion — is what separates the carArth KB from a scraped content dump.

4.2 The Three-Tier Confidence System

Not all knowledge is equal. The carArth KB enforces a three-tier confidence hierarchy that directly governs how the agent uses each chunk:

Tier	Source Types	Agent Behaviour
High	Government portals (Parivahan, IRDAI, VAHAN, FADA, MORTH), ARAI, BNCAP, Global NCAP, carArth proprietary data	Stated as fact with direct source citation
Medium	Verified automotive publications (Autocar India, CarWale, ET Auto), manufacturer specs	Qualified: <i>"According to Autocar India..."</i>
Low	Reddit, YouTube, forums, owner reviews	Aggregated only: <i>"Based on [N] owner reviews..."</i>

Table 3: Knowledge Base Confidence Tier System

This tiering system prevents the most dangerous failure mode of RAG-based agents: presenting unverified opinion as fact. In a financial decision context, this distinction is not cosmetic — it is the difference between trustworthy advice and harmful misinformation.

4.3 Why 40,000 Reviews + 1,000 Expert Reviews Are the Moat

The SUV use case demonstrates something no competitor can replicate quickly: **the granularity of carArth's review corpus.**

When a buyer asks *"how is the AC?"* — a question that sounds trivial but drives real purchase anxiety in Hyderabad's climate — carArth can answer with:

- 127 owner reviews specifically from Hyderabad owners (not pan-India averages)
- Filtered by fuel type (diesel AC compressor behaviour differs from petrol)
- Stratified by mileage bracket (early-life vs. high-mileage AC performance differs)

- Cross-referenced against the expert review's specific test data

No other Indian used car platform has this level of granularity. Not Cars24. Not CarDekho. Not Droom[10][11]. Building this corpus required months of structured scraping, GPT-4o-mini sentiment extraction, and QA validation. It cannot be replicated in weeks.

5. The Living Knowledge System

5.1 The TTL (Time-to-Live) System

Knowledge has a shelf life. Government fee schedules change. RTO processes get digitised. Insurance premiums fluctuate. A knowledge base that doesn't acknowledge staleness is a liability, not an asset.

The TTL system assigns every chunk a lifespan:

Content Type	TTL (days)	Rationale
Government process/fees	180	RTO fee revisions typically annual
Insurance rules (IRDAI)	365	Regulatory cycle
Safety ratings	730	NCAP test results are stable
Live price data	7	Market moves weekly
Price reasoning chunks	90	Macro trends shift quarterly
Owner reviews	180	Model reputation evolves
EV-specific data	90	Rapidly evolving market

Table 4: TTL Assignment by Content Type

Every night at 2 AM IST, the TTL sweeper runs:

```
UPDATE knowledge_chunks
SET status = 'stale',
confidence_tier = CASE
WHEN confidence_tier = 'high' THEN 'medium'
ELSE confidence_tier
```

END

```
WHERE last_updated < NOW() - (ttl_days || ' days')::INTERVAL  
AND status = 'active';
```

Stale chunks are never deleted — they are downgraded. The agent appends *"Last verified [date] — recommend confirming with source"* to any response drawn from a stale chunk. This is transparency by design, not by accident.

5.2 The Three Weekly Rituals

The KB is not a project. It is a practice. Three institutionalised rituals prevent decay:

- **Every Monday 9 AM IST:** 60-minute chunk audit — 20 random chunks verified for source accuracy and content freshness
- **Every Wednesday 9 AM IST:** Failed query review — top 5 weekly failures become new chunk briefs
- **Every Night 2 AM IST:** Automated TTL sweeper — stale chunks downgraded, never silently wrong

"The KB is never done. The team that maintains it is the product."

5.3 The Failed Query Flywheel

The most important quality instrument in the KB is not the QA checklist — it is the failed query log. Every time a user query is not answered satisfactorily by the KB, it is logged:

Failure Type	Definition	Action
kb_gap	No relevant chunk exists	New chunk assigned to researcher
low_confidence	Retrieval score < 0.75	Chunk quality improvement
wrong_answer	Chunk returned but answer incorrect	Chunk removed, replaced
hallucination	Agent fabricated a fact	Guardrail added or source chunk fixed
web_fallback	Agent fell back to web search	New chunk created to internalise

Table 5: Failed Query Classification and Response Protocol

Every Wednesday, the QA Lead reviews the top 5 failures from the past week. Each becomes a new chunk brief. The KB learns from every gap — it is not a static document repository but a continuously improving intelligence system.

This creates a compounding flywheel: more users → more queries → more gap discoveries → faster KB growth → better agent performance → more users.

6. The Road to 11,230 Chunks: Phased Build Plan

Phase	Chunks Added	Timeline	Key Additions
Current	4,020	Live	Buying guide, seed reviews, pricing pipeline, safety ratings
Phase 1	+3,210	April 3, 2026	Full owner review corpus (4,800 total), expert reviews (1,200 total), RTA rules (1,440 total)
Phase 2	+2,400	May–June 2026	Insurance intelligence, finance products, city expansion (5 cities), EV full coverage
Phase 3	+1,600	June–July 2026	Dealer intelligence, scrappage policy, CAFÉ regulations
Full target	11,230	July 2026	Complete coverage across all 12 categories

Table 6: Knowledge Base Phased Expansion Plan

7. What Makes This Knowledge Base a Moat

The carArth KB is not replicable quickly. Here is why:

7.1 Provenance

Every chunk has a source URL that was live and verified at creation. Competitors cannot copy this because they cannot copy the verification chain. A knowledge base without provenance is a liability in a regulated context — ours is an asset.

7.2 Confidence Tiering

The three-tier system is not a labelling exercise — it is an epistemological architecture. It determines how the agent communicates uncertainty, which directly affects user trust. Building this requires editorial discipline that cannot be automated or rushed.

7.3 The Proprietary Pricing Signal

The aggregatedcars table — carArth's own aggregated listings database — is the most accurate real-time used car pricing source in India. No competitor has this data for the same breadth of platforms. The pricing intelligence derived from it is a moat that compounds with every new listing ingested.

7.4 The Failed Query Flywheel

Every user interaction that exposes a KB gap creates a new chunk brief. The more users interact with Ms. 7, the faster the KB grows, the better Ms. 7 becomes, the more users interact. This is a data flywheel that widens the gap between carArth and any new entrant with every passing week.

7.5 The Review Corpus Depth

40,000 owner reviews and 1,000+ expert reviews — aggregated, structured, and queryable at city-fuel-theme-model granularity — cannot be replicated without months of focused data engineering and QA effort. This is carArth's single largest defensive asset.

8. Early Results and Validation

The carArth KB launched its first production queries in March 2026 against a seed corpus of 2,355 chunks. Early performance metrics from internal testing:

Metric	Target	Achieved (Seed Phase)
Retrieval quality pass rate	80% on 50 real queries	74% — improving daily
Failed query rate	\$<\$20%	22% — within 2% of target
Stale chunk rate	\$<\$15%	8% — well within target
Schema compliance	100%	97% — 3 legacy chunks being fixed
Source URL live rate	100%	99.1% — 2 government pages temporarily down

Table 7: Knowledge Base Early Performance Metrics (March 2026)

The retrieval quality is expected to cross 80% by March 27, 2026 — one week before the full KB go-live target of April 3, 2026.

9. The Road Ahead: From Knowledge Base to Knowledge Network

At 11,230 chunks, the carArth KB becomes the most comprehensive structured knowledge base for the Indian used car market in existence. But the vision extends beyond a single market.

Phase 2 (July–December 2026): The Dealer Intelligence Layer

India has over 20,000 unorganised used car dealers — a segment that has received zero AI tooling. The carArth KB will expand to serve dealer-facing queries: demand intelligence by locality, pricing guidance, inventory turnover benchmarks, and buyer intent signals derived from Ms. 7 interaction data.

Phase 3 (2027): The Lender Intelligence Layer

For banks and NBFCs extending used car loans, the carArth KB — combined with the aggregatedcars pricing data and Ms. 7 interaction signals — represents a structured asset intelligence layer. A lender using carArth data can evaluate vehicle value and buyer intent with a precision currently unavailable from any Indian source.

Phase 4 (2027): The Open Knowledge API

The carArth knowledge infrastructure — the chunk schema, the confidence tier system, the TTL methodology — is generalisable beyond used cars. As the KB matures, carArth will explore making a curated subset available via API to developers building India-specific automotive applications — establishing carArth as the knowledge infrastructure layer for the broader Indian automotive ecosystem.

10. Conclusion

The 11,230-chunk knowledge base is not a back-end technical asset. It is the core product.

Ms. 7 is only as trustworthy as the knowledge she retrieves. Master 7 is only as accurate as the market signals that feed his deal scoring. The buyer experience is only as reliable as the verification chain behind every fact the agent asserts.

India's used car market has never had an honest advisor. Not because the technology didn't exist — but because no one had assembled the knowledge infrastructure to make honesty at scale possible.

That infrastructure is being built now. Chunk by chunk, source by source, state by state.

At 4,020 chunks today, growing to 11,230 by July 2026, the carArth knowledge base is not yet complete. But it is already the most structured, verified, and India-specific automotive knowledge corpus in the country.

And the team that builds it, maintains it, and grows it — is the product.

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About carArth

carArth is India's first buyer-neutral used car search engine and AI advisory platform. Founded in 2025 and headquartered in Hyderabad, carArth aggregates listings from every major platform — Cars24, Spinny, OLX, CarDekho, and independent dealers — and provides verified, unbiased market intelligence to help buyers make informed decisions.

Unlike traditional platforms optimised for transaction volume, carArth is optimised for buyer outcomes. The company's AI agents —

Ms. 7 (buyer advisor) and Master 7 (market analyst) — are powered by India's most comprehensive structured automotive knowledge base, built from 11,230 verified chunks covering regulatory procedures, pricing intelligence, safety ratings, owner reviews, and market signals.

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