NHOS Oracle Matrix Search Engine™

A Local Hybrid Retrieval and Contextual Discovery Architecture for Personal Health Knowledge

Technical Research White Paper

Architecture, Methodology & Validation Framework (v1.0)

NHOS Labs, Inc.
NHOS Intelligence Matrix Engine™ Research Program
Version 1.0 — September 2026
Research Stage: Implemented Research System & Validation Framework

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Evidence Status Notice

NHOS Oracle Matrix Search Engine™ is an implemented research system within the NHOS ecosystem. This paper documents its architecture, retrieval methodology, implemented capabilities, and proposed evaluation framework. Implementation status should not be interpreted as empirical validation. Formal benchmarking, human relevance evaluation, confidence calibration, comparative baseline testing, privacy/network measurement, scalability evaluation, and other proposed assessments remain subject to the validation program described in this paper.

Executive / Research Abstract

Health information environments are increasingly characterized by fragmentation across conditions, symptoms, remedies, herbs and supplements, medications, medication–herb interactions, traditional medicine systems, protocols, wellness records, and other heterogeneous information structures. Conventional keyword search can retrieve exact textual matches but may perform poorly when users misspell terms, use partial concepts, formulate multi-concept queries, or require results to be ranked according to domain-specific characteristics.

NHOS Oracle Matrix Search Engine™ is an implemented local health-information retrieval and contextual discovery system developed within the NHOS Intelligence Matrix Engine™ (NIME™) research program. Oracle is designed to provide domain-specific discovery across a heterogeneous NHOS health-knowledge environment while prioritizing local execution, local persistence, user control, and minimized dependence on centralized behavioral profiling.

The current implementation, NHOS Oracle Matrix Search Engine v6.3, combines two principal retrieval pathways. The first is a hybrid lexical/fuzzy retrieval pathway incorporating exact and content matching, title and excerpt weighting, token-level matching, Levenshtein-distance fuzzy matching, category weighting, and type-specific ranking boosts. The second is the NHOS Matrix Engine, which parses multi-concept queries into multiple tokens and evaluates those concepts against an operational representation of each indexed knowledge item. The implementation also contains an optional NHOS Recommendations layer that uses locally retained interaction history, recent queries, selected results, and category patterns to generate contextual suggestions.

Oracle is therefore not characterized in this paper as a semantic-search, embedding-based, vector-retrieval, or machine-learning retrieval system. Its current demonstrable methodology is more precisely described as **hybrid lexical and fuzzy retrieval with domain-aware weighting, matrix-based multi-concept matching, and local contextual recommendation logic.**

The present paper documents the architecture, data model, retrieval methodology, ranking framework, Matrix Engine, recommendation mechanism, local analytics, user-facing capabilities, privacy-oriented design, limitations, safety boundaries, and proposed empirical validation methodology. It intentionally does not claim that Oracle currently demonstrates superior retrieval performance, clinical effectiveness, recommendation quality, calibrated confidence, or improved health outcomes.

The principal research proposition is that a domain-specific hybrid retrieval architecture can support useful personal health-knowledge discovery while operating within a local-first environment that minimizes unnecessary centralized collection of user interaction data. This proposition remains an empirical question. Formal benchmarking is therefore proposed as a subsequent research phase, including relevance judgments, precision/recall analysis, ranking metrics, confidence calibration, ablation studies, latency measurement, error analysis, and

comparison with established retrieval baselines.

This is a working hypothesis, not a claim of completed scientific validation.

Keywords

health information retrieval, hybrid retrieval, fuzzy matching, Levenshtein distance, local-first software, personal health knowledge, knowledge discovery, domain-aware ranking, multi-concept search, contextual recommendation, privacy-oriented architecture, NIME™, NHOS Oracle.

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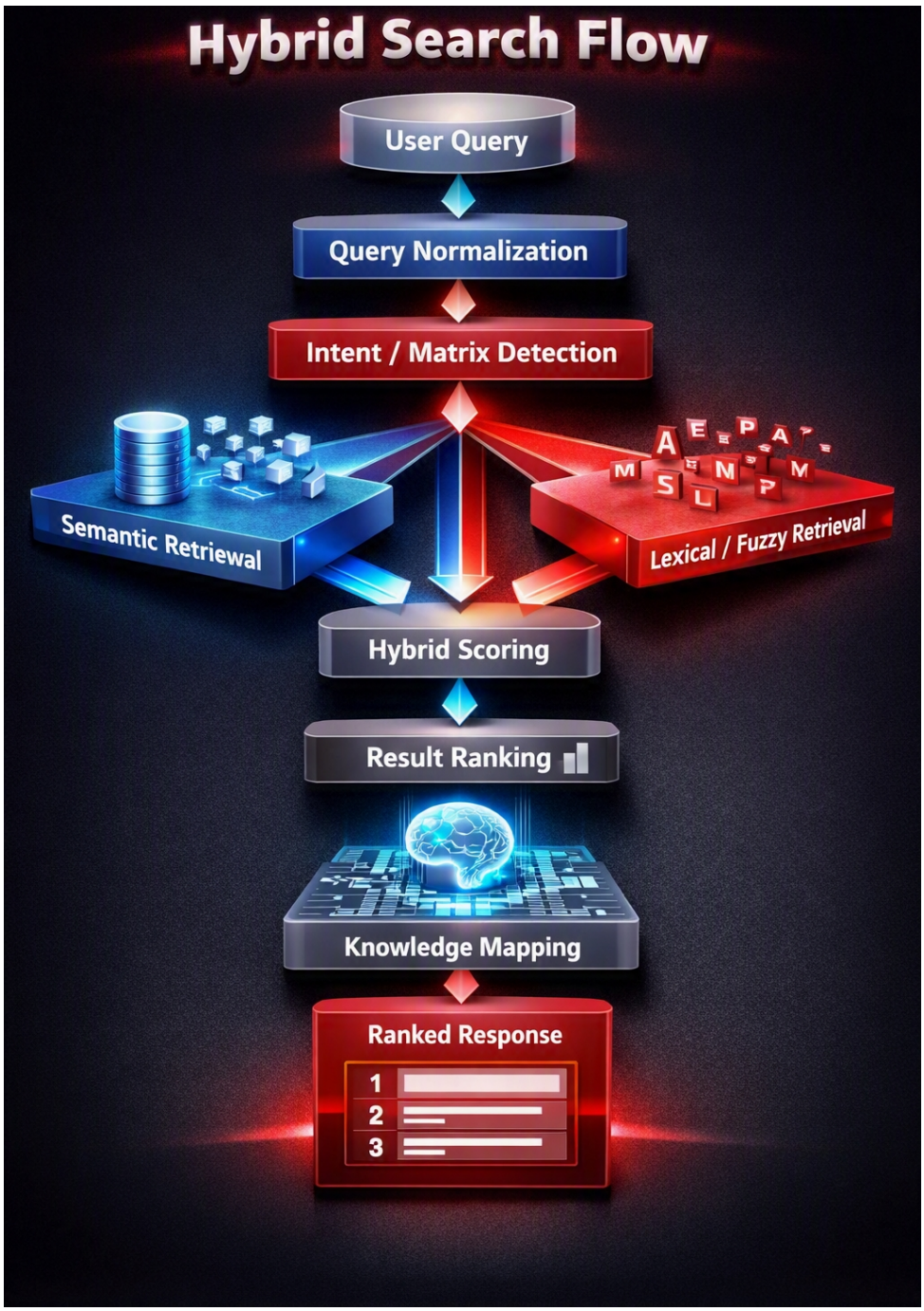

Part I: Research Foundation

1. Introduction

Access to health information increasingly involves navigating heterogeneous information sources rather than retrieving a single class of documents. A user may begin with a symptom, move toward possible conditions, investigate natural remedies, examine an herb or supplement, check medication interactions, explore a traditional medicine system, review a protocol, or compare information with previously recorded wellness observations. These information objects are related, but they are not structurally identical.

A conventional search interface can treat them as text. A health-information environment, however, can treat them as **typed knowledge objects with domain-specific relationships**. This distinction provides the motivation for NHOS Oracle.

Oracle was developed as a retrieval and discovery layer within the broader NHOS Intelligence architecture. Its purpose is not merely to provide a search box over a collection of strings, but to provide a unified retrieval interface across heterogeneous health knowledge while retaining the ability to recognize different object types and route users toward specialized NHOS tools.

The current implementation identifies itself as **NHOS Oracle Matrix Search Engine v6.3**, with the release designated the "NHOS Recommendations Edition." The deployed interface exposes Hybrid, Matrix, Clinical, and NHOS Recommendations modes.

The implementation is therefore best understood as an **implemented research system** rather than as a completed scientific validation study. That distinction is fundamental to this paper. The existence of an operational algorithm demonstrates that the architecture has been implemented. It does not, by itself, establish that the algorithm is superior to alternative retrieval approaches.

Accordingly, this paper adopts the NHOS research principle: **Build transparently. Measure rigorously. Report proportionally.**

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2. Research Motivation

2.1 Fragmented Health Knowledge

Personal health-information discovery frequently crosses information boundaries. A query concerning "joint pain" might reasonably produce:

- A symptom record
- A condition

- An herb or supplement
- A protocol
- An interaction
- A traditional medicine concept
- A wellness record

A conventional lexical search engine may identify textual similarity, but it does not inherently understand that these objects belong to different health-information categories. Oracle introduces explicit type and category information into retrieval.

The current implementation aggregates multiple NHOS knowledge structures into a common search representation, including conditions, herbs, symptoms, medications, medication–herb interactions, traditional medicine systems, protocols, wellness/tracking records, and saved items. This enables Oracle to operate as a **cross-domain health knowledge discovery layer**.

2.2 Imperfect User Queries

Health queries are rarely guaranteed to be clean. Users may:

- misspell terms;
- enter partial terms;
- use alternate wording;
- combine several concepts;
- use natural-language fragments;
- search using symptom clusters;
- or remember only part of a health-related term.

Oracle therefore combines several forms of lexical matching rather than depending solely on exact equality.

2.3 The Local-First Research Question

Most modern information systems increasingly depend on centralized infrastructure. NHOS investigates an alternative architecture in which useful intelligence can be performed locally where functionally appropriate. Local-first software research has similarly explored models emphasizing user ownership, offline capability, privacy, and local control rather than making centralized storage the default architectural assumption.

Within NHOS, local execution is not presented as proof of complete privacy or security. Rather, it is an architectural design objective that can reduce unnecessary data movement. This distinction is consistent with established privacy-engineering approaches, which treat privacy as a systems-engineering and risk-management problem rather than merely as a feature label.

2.4 The Need for the 1st White Paper

The previous NHOS Oracle papers documented Oracle v6.3, the Matrix Engine, Hybrid Retrieval, Recommendations, Local-first architecture, and a Validation framework. But they did **not** document:

- Oracle as a tri-layer architecture;
- Oracle v6.3+ → v7.0 evolution;
- Expanded NHOS v18+ knowledge environment;
- New retrieval modes;
- New recommendation logic;
- New offline architecture;
- New privacy model;
- New evaluation framework;
- New reproducibility protocol;
- or a New research roadmap.

This 1st White Paper fills that gap by providing a definitive, comprehensive, and updated documentation of the system.

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3. Problem Definition

The research problem addressed by Oracle can be stated as follows:

How can heterogeneous personal-health knowledge be retrieved and ranked using domain-specific lexical and fuzzy methods while supporting multi-concept queries and contextual discovery within a local-first execution environment?

This problem contains several sub-problems:

1. How should heterogeneous health objects be represented within a unified retrieval index?

2. How should exact textual matches be prioritized?
3. How should individual query tokens contribute to relevance?
4. How should approximate or misspelled terms be recognized?
5. How should health-domain categories influence ranking?
6. How should object type influence ranking?
7. How should multiple simultaneous health concepts be represented?
8. How should locally retained interaction history contribute to contextual discovery?
9. How should confidence-like scores be communicated without implying statistical probability?
10. How should the system be evaluated empirically?

Oracle provides an implemented architecture through which these questions can be investigated.

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4. Research Gap

Hybrid information retrieval is not a new concept, and fuzzy string matching is not a new computational technique. Likewise, recommendation systems and personalized search have extensive prior literature.

The potential research interest of Oracle therefore does **not** lie in claiming invention of these underlying techniques. The research interest lies in their composition within a particular architectural environment:

Heterogeneous health knowledge, **lexical and fuzzy retrieval**, **domain-aware weighting**, **multi-concept Matrix processing**, **local interaction context**, and **local-first execution**.

This creates a domain-specific research system whose behavior can subsequently be measured.

The paper therefore frames Oracle as an **architecture for investigating domain-specific health-information retrieval and contextual discovery**, rather than as a claim that NHOS has invented hybrid search.

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5. Research Questions

The Oracle research program proposes the following primary research question:

RQ1 — Hybrid Retrieval Effectiveness

Can a domain-specific hybrid lexical/fuzzy retrieval architecture provide effective retrieval across heterogeneous personal health knowledge?

Secondary questions include:

RQ2 — Fuzzy Matching Contribution

Does fuzzy matching improve retrieval of relevant results for misspelled or approximate queries?

RQ3 — Category Weighting Contribution

Does domain-specific category weighting improve the ranking of relevant health-information objects?

RQ4 — Type-Specific Boosting Contribution

Do type-specific ranking boosts improve retrieval usefulness across heterogeneous health-information categories?

RQ5 — Multi-Concept Processing Effectiveness

Can Matrix-based multi-concept processing effectively identify knowledge objects associated with multiple simultaneous query concepts?

RQ6 — Confidence Calibration

How strongly does Oracle's internally calculated confidence score correlate with independently judged relevance?

RQ7 — Local Contextual Recommendation Effectiveness

Can locally maintained interaction history generate contextually useful recommendations without requiring routine centralized behavioral profiling?

RQ8 — Component Contribution Analysis

What retrieval-performance contribution is attributable to each major component of the hybrid architecture?

RQ9 — Failure Modes

What failure modes emerge from fuzzy matching, domain weighting, type boosting, Matrix processing, and contextual recommendation?

RQ10 — Offline Retrieval Capability

Can the architecture maintain useful retrieval functionality under offline or connectivity-constrained conditions when the required knowledge is already available locally?

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6. Research Objectives

The 1st NHOS Oracle White Paper defines the following research objectives:

6.1 Objective 1 — Document the Oracle Architecture

Provide a complete technical description of the NHOS Oracle Matrix Search Engine™, including hybrid retrieval, Matrix Engine, Recommendations Engine, local-first architecture, offline capability, privacy model, and security boundaries.

6.2 Objective 2 — Establish a Scientific Validation Framework

Define a reproducible validation methodology including benchmark datasets, relevance judgments, precision/recall, MRR/nDCG, confidence calibration, Matrix evaluation, ablation studies, baseline comparisons, recommendation evaluation, privacy/network evaluation, offline evaluation, and performance evaluation.

6.3 Objective 3 — Identify Limitations and Failure Modes

Document known limitations, failure modes, and architectural boundaries.

6.4 Objective 4 — Provide a Reproducibility Protocol

Define reproducibility requirements including Oracle version, knowledge-base version, browser, operating system, device class, local state, enabled modes, benchmark version, and expected vs. observed results.

6.5 Objective 5 — Position Oracle within NIME™

Describe how Oracle fits within the broader NHOS Intelligence Matrix Engine™ architecture.

6.6 Objective 6 — Define a Research Roadmap

Provide a Q4 2026–Q2 2027 validation roadmap.

6.7 Objective 7 — Support Explainable Retrieval

Document how Oracle's architecture supports explainability.

6.8 Objective 8 — Provide a Scientific Interpretation

Define the scientific interpretation of Oracle as an implemented research system.

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7. Scope and Delimitations

7.1 Scope

This paper covers the Oracle Hybrid Retrieval Engine, NHOS Matrix Engine, NHOS Recommendations Engine, local-first architecture, offline capability, privacy model, security boundaries, knowledge aggregation, indexing, query processing, ranking, confidence scoring, multi-concept processing, contextual recommendation, local analytics, autocomplete, voice search, filtering and sorting, clinical mode, knowledge discovery routing, export architecture, sharing, reproducibility, validation methodology, and research roadmap.

7.2 Delimitations

This paper does **not** claim clinical effectiveness, diagnostic accuracy, treatment appropriateness, evidence quality, probability-calibrated confidence, superiority to semantic/vector retrieval, superiority to BM25 or TF-IDF, privacy/security superiority, or improved health outcomes. These require controlled validation.

7.3 Implementation vs. Validation

This paper distinguishes between **Implemented**, **Measured**, **Preliminary evidence**, **Validation planned**, and **Future research** capabilities.

7.4 NHOS Oracle Matrix Search Engine as an Implemented Research System

NHOS Oracle Matrix Search Engine is an implemented research system. It is **not** a completed scientific validation study.

7.5 Local-First Architecture Delimitations

Local-first execution does not imply complete privacy, complete security, absence of network communication, resistance to device compromise, resistance to malicious extensions, secure deletion, or encryption at rest. These require separate evaluation.

7.6 Offline Capability Delimitations

Offline capability depends on cached assets, local knowledge availability, browser behavior, and device behavior. Offline capability must be measured, not assumed.

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8. Architectural Positioning within NIME™

NHOS Oracle is positioned as a retrieval and discovery subsystem within the broader **NHOS Intelligence Matrix Engine™ (NIME™)** research program.

The distinction is important. NIME™ represents the broader intelligence architecture. Oracle represents a specific implemented research system concerned primarily with knowledge indexing, retrieval, ranking, multi-concept matching, contextual discovery, and user interaction with heterogeneous health knowledge.

8.1 NIME™ Architectural Hierarchy

8.2 NIME™ Responsibilities

NIME™ provides structured knowledge, typed knowledge objects, category definitions, metadata schemas, domain semantics, evidence references, knowledge relationships, and intelligence orchestration.

Oracle consumes these structures and provides retrieval, ranking, multi-concept processing, contextual discovery, navigation, local analytics, and offline capability.

8.3 Oracle's Role within NIME™

Oracle is responsible for indexing NIME™ knowledge, interpreting user queries, retrieving relevant objects, ranking results, calculating confidence, processing multi-concept queries, generating contextual recommendations, and routing users to specialized NHOS tools.

8.4 Oracle as the "Front Door" to NHOS Intelligence

Oracle serves as the primary entry point into NHOS intelligence. Users often begin with a search query, and Oracle determines which knowledge objects are relevant, which NHOS tools should be invoked, which contextual suggestions should be displayed, which concepts were matched, and how results should be ranked.

8.5 Oracle's Architectural Distinction

Oracle is not a semantic search engine, embedding-based retrieval system, vector database, machine-learning recommender, or clinical decision-support system. Oracle is a hybrid lexical/fuzzy retrieval system, a multi-concept processing system, a local contextual recommendation system, and a local-first health-intelligence architecture.

Part II: Oracle Architecture & Retrieval

9. Oracle System Architecture

Oracle can be conceptualized as a **five-layer architecture**:

1. **Knowledge Aggregation Layer**

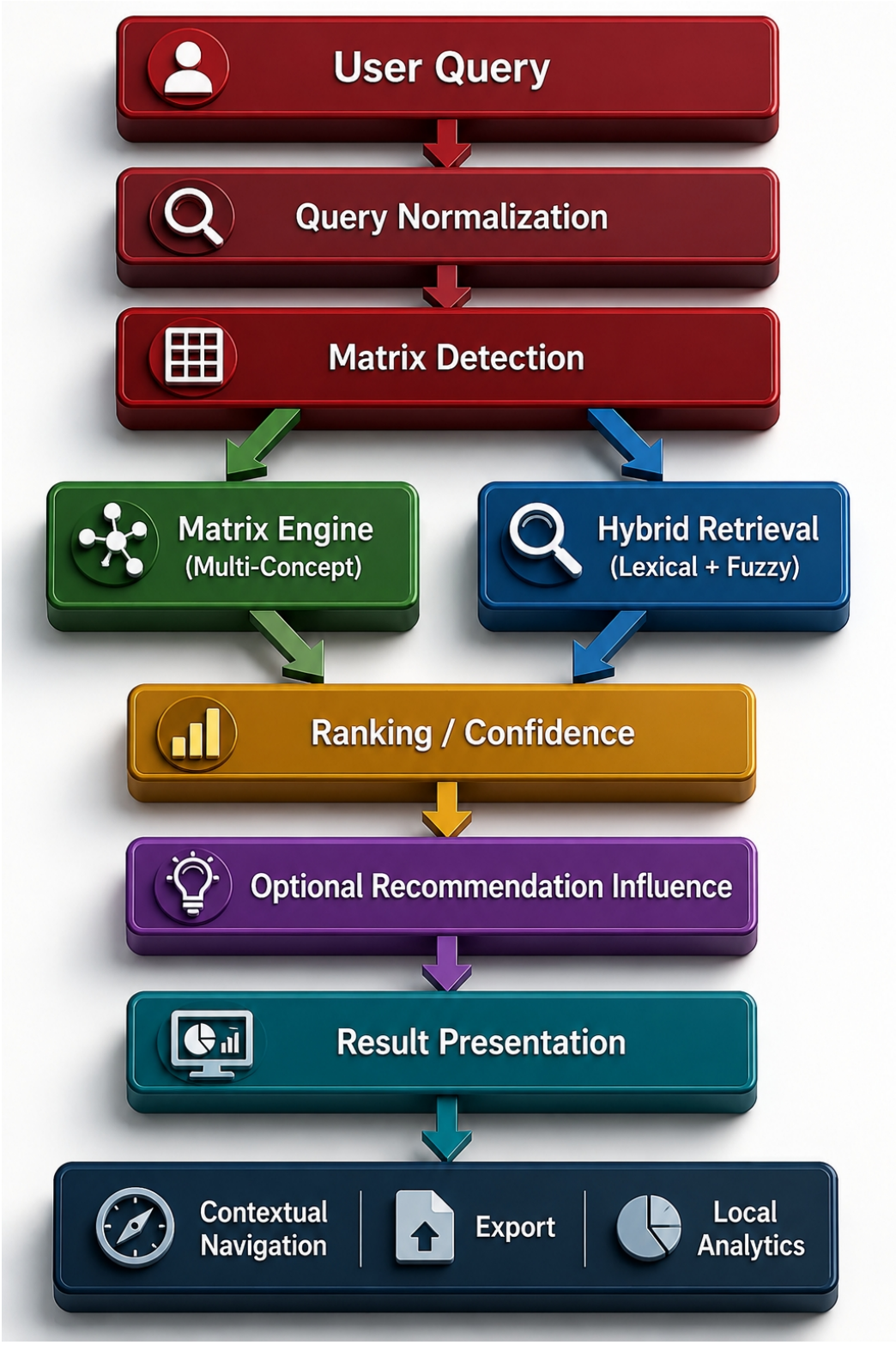
2. **Hybrid Retrieval Layer**

3. **NHOS Matrix Engine Layer**

4. **NHOS Recommendations Layer**

5. **Interaction & Orchestration Layer**

9.1 High-Level Architecture Diagram



9.2 Architectural Principles

Oracle is designed around several principles: local-first execution, typed heterogeneous knowledge, hybrid lexical/fuzzy retrieval, multi-concept processing,

domain-aware ranking, contextual discovery, explainability, offline capability, and privacy-oriented architecture.

9.3 Oracle v6.3 → v7.0 Evolution

The current production implementation documented in this paper is Oracle v6.3. The v7.0 designation refers to the architectural evolution and planned next-stage implementation, not to a completed v7.0 release. The planned evolution includes expanded category weighting, improved fuzzy matching, enhanced Matrix coverage, deterministic recommendation logic, expanded local analytics, improved offline behavior, expanded export formats, improved Clinical Mode, expanded knowledge taxonomy, and an improved indexing pipeline.

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10. System Components

Oracle consists of five major components.

10.1 Component 1 — Knowledge Aggregation Layer

This layer aggregates all available NHOS knowledge objects and converts them into a common searchable representation.

Knowledge Sources Include:

Knowledge Type	Description
Conditions	Structured condition knowledge
Herbs/Supplements	Herbal profiles, remedy information
Symptoms	Symptom categories and mappings
Medications	Pharmaceutical knowledge
Medication–Herb Interactions	Interaction records
Traditional Medicine Systems	Ayurveda, TCM, etc.
Protocols	Locally stored health protocols
Wellness Records	User-generated tracking entries
Saved Items	User-saved knowledge objects

Indexed Representation Includes:

- identifier;
- type;
- title;
- excerpt;
- searchable content;
- category;
- category weight;
- metadata.

This creates a typed heterogeneous knowledge index.

10.2 Component 2 — Hybrid Retrieval Layer

The hybrid retrieval layer evaluates queries using exact matching, title/excerpt matching, token-level matching, fuzzy matching, category weighting, and type-specific boosting. This layer produces a base hybrid score, algorithmic confidence, and ranked results.

10.3 Component 3 — NHOS Matrix Engine Layer

The Matrix Engine processes multi-concept queries using delimiter-based concept parsing, concept normalization, concept-by-concept matching, matched-concept tracking, and concept coverage calculation. This layer produces a Matrix score, Matrix confidence, and matched-concept indicators.

10.4 Component 4 — NHOS Recommendations Layer

The recommendation layer uses local interaction history, recurring categories, recurring query terms, deterministic heuristics, and contextual explanations. This layer produces contextual suggestions, recommendation confidence, and optional ranking influence.

10.5 Component 5 — Interaction & Orchestration Layer

This layer provides result preview, filtering, sorting, saving, export, sharing, navigation to NHOS tools, local analytics, clinical mode, voice search, and autocomplete.

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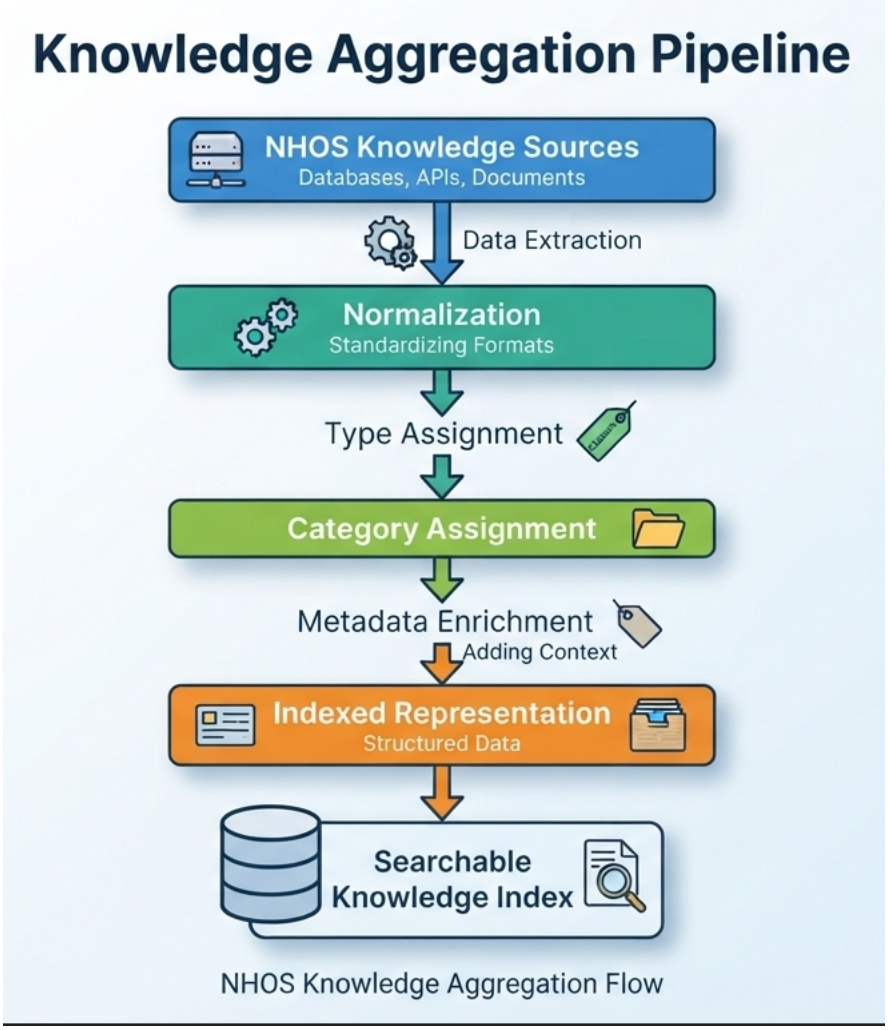
11. Knowledge Aggregation Architecture

11.1 Knowledge Aggregation Pipeline



11.2 Knowledge-Source Taxonomy

Source	Description	Example Fields
Conditions	Structured condition knowledge	title, symptoms, remedies
Herbs	Herbal profiles	title, uses, interactions
Symptoms	Symptom categories	title, related conditions
Medications	Pharmaceutical knowledge	title, interactions
Interactions	Medication–herb interactions	pairs, severity
Traditions	Traditional medicine systems	concepts, mappings
Protocols	Local protocols	steps, ingredients
Wellness	User tracking	notes, metrics
Saved Items	User-saved objects	metadata

11.3 Index Construction

Index construction includes title extraction, excerpt generation, content aggregation, category assignment, category weight assignment, type-specific metadata, and searchable content construction.

11.4 Index Structure Table

Field	Description
id	unique identifier
type	knowledge-object type
title	primary title
excerpt	short summary
content	full searchable content
category	domain category
categoryWeight	ranking multiplier
metadata	additional fields

12. Knowledge-Source Taxonomy

The NHOS Oracle Matrix Search Engine™ operates over a heterogeneous knowledge environment. Oracle does not rely on a single homogeneous database; instead, it aggregates multiple NHOS knowledge structures into a unified, typed, domain-aware index.

12.1 Knowledge Categories

Oracle currently aggregates knowledge from the following NHOS categories:

Category	Description	Example Objects
Conditions	Structured condition knowledge	Arthritis, Migraine, GERD
Herbs/Supplements	Herbal profiles, natural remedies	Turmeric, Ashwagandha
Symptoms	Symptom categories and mappings	Joint pain, Fatigue
Medications	Pharmaceutical knowledge	Ibuprofen, Metformin
Medication–Herb Interactions	Interaction records	St. John's Wort × SSRI
Traditional Medicine Systems	Ayurveda, TCM, naturopathy	Dosha concepts, meridian maps
Protocols	Locally stored health protocols	Detox protocol, sleep protocol
Wellness Records	User-generated tracking entries	Sleep logs, mood logs
Saved Items	User-saved knowledge objects	Bookmarks, saved herbs

12.2 Knowledge-Object Types

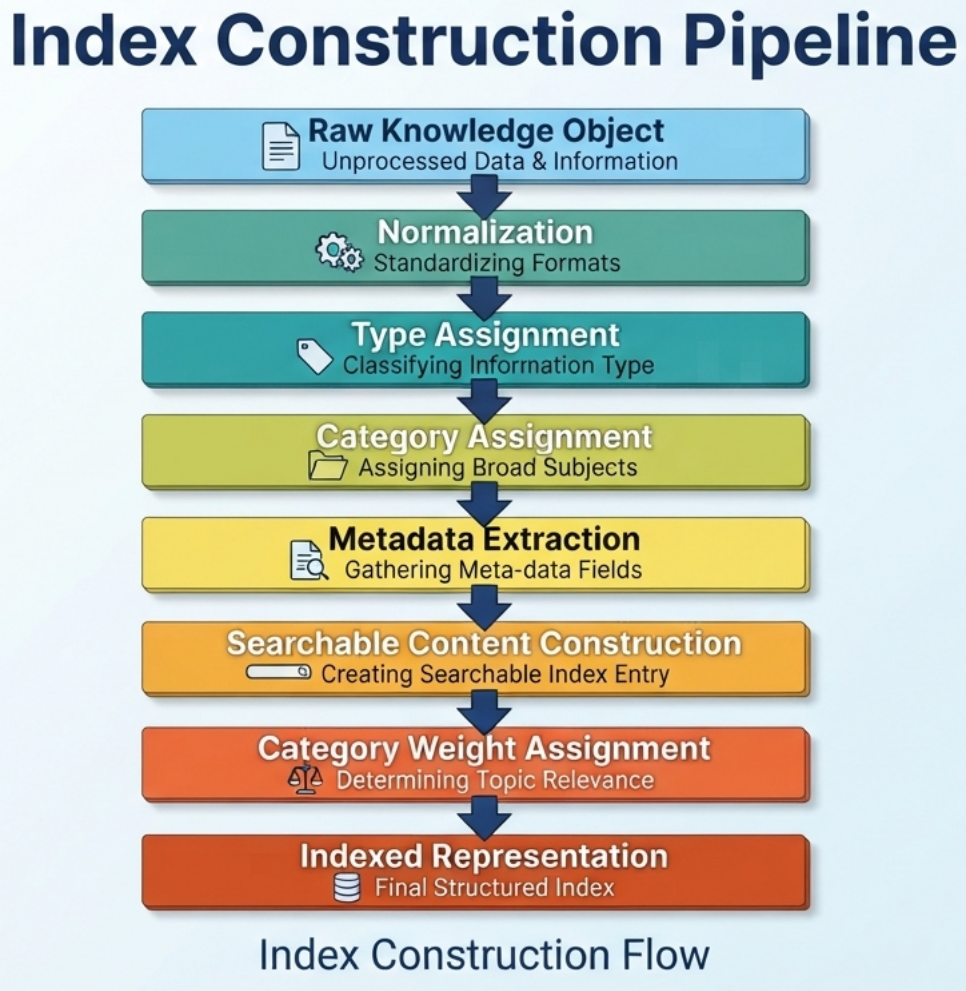
Oracle assigns each indexed object a **type**, which influences category weighting, type-specific boosting, ranking, and routing to NHOS tools.

Type	Description
condition	Structured condition knowledge
herb	Herbal profile
symptom	Symptom category
medication	Pharmaceutical knowledge
interaction	Medication–herb interaction
tradition	Traditional medicine concept
protocol	Local protocol
wellness	User-generated record
saved	User-saved item

12.3 Knowledge-Source Taxonomy Diagram

13. Index Construction

13.1 Index Construction Pipeline



13.2 Indexed Representation Fields

Field	Description
id	Unique identifier
type	Knowledge-object type
title	Primary title
excerpt	Short summary
content	Full searchable content
category	Domain category

Field	Description
categoryWeight	Ranking multiplier
metadata	Additional fields

13.3 Example Indexed Object

json

{ "id": "herb_0231", "type": "herb", "title": "Turmeric", "excerpt": "Anti-inflammatory herb used for joint pain and digestive support.", "content": "Turmeric (Curcuma longa) is a natural anti-inflammatory herb...", "category": "herbs", "categoryWeight": 1.5, "metadata": { "synonyms": ["Curcuma longa"], "interactions": ["NSAIDs"], "evidence": "traditional" }}

13.4 Category Weight Table

Category	Weight
Herbs	**1.5**
Symptoms	**1.3**
Medications	**1.2**
Interactions	**1.4**
Traditions	**1.3**
Protocols	**1.2**
Wellness	**1.1**
Saved Items	**1.8**

These weights are engineering parameters, not evidence grades.

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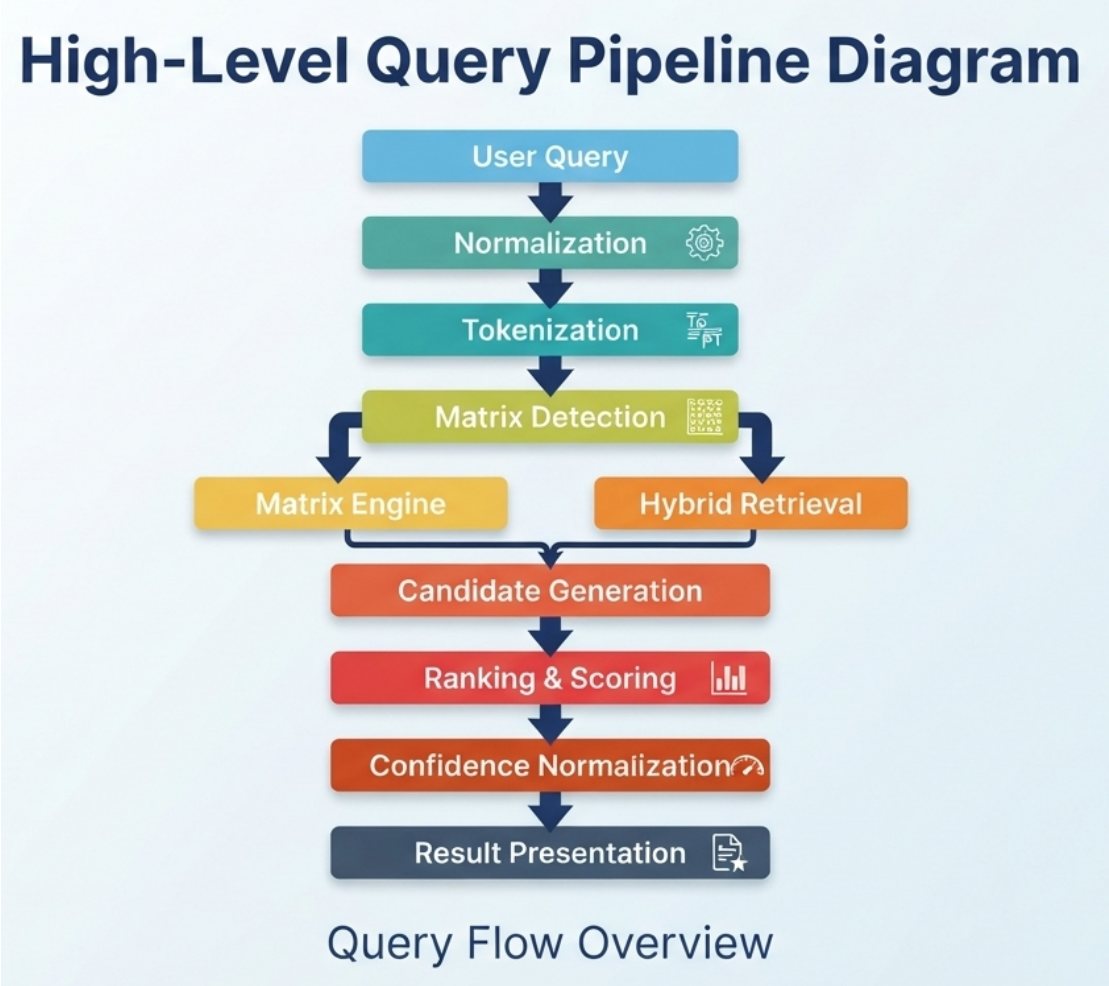
14. Query Processing Pipeline

14.1 High-Level Query Pipeline Diagram



14.2 Pipeline Stages

Oracle's query-processing pipeline consists of Normalization, Tokenization, Matrix Detection, Hybrid Retrieval, Candidate Generation, Ranking & Scoring, Confidence Normalization, and Result Presentation.

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15. Normalization and Tokenization

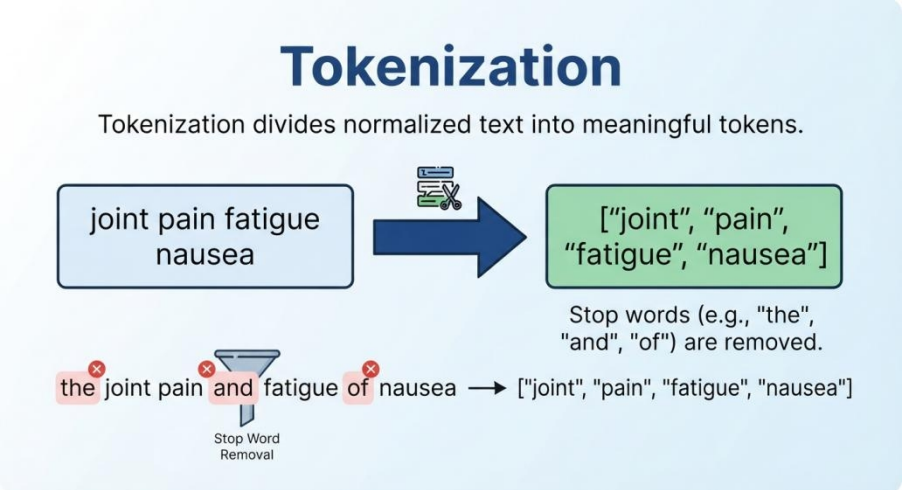
15.1 Query Normalization

Normalization includes converting text to lowercase, removing punctuation, removing special characters, trimming whitespace, and collapsing multiple spaces.

text

"Joint Pain, Fatigue; Nausea"→ "joint pain fatigue nausea"

15.2 Tokenization



15.3 Tokenization Table

Input	Normalized	Tokens
"Joint Pain"	"joint pain"	["joint", "pain"]
"Fatigue; Nausea"	"fatigue nausea"	["fatigue", "nausea"]
"Ashwagandha root"	"ashwagandha root"	["ashwagandha", "root"]

16. Exact Matching

Exact matching checks whether the full query appears in content, title, or excerpt.

16.1 Exact Matching Scores

Condition	Score
Content contains full query	+35
Title contains full query	+20
Excerpt contains full query	+15
Exact title equality	+15

These are implementation constants.

---

17. Title and Excerpt Matching

17.1 Title/Excerpt Matching Table

Condition	Score
Title contains token	+10
Title starts with token	+8
Excerpt contains token	+6
Excerpt starts with token	+5

18. Token-Level Matching

18.1 Token Matching Contributions

Condition	Score
Content contains token	+5
Token appears in metadata	+3
Token appears in synonyms	+2

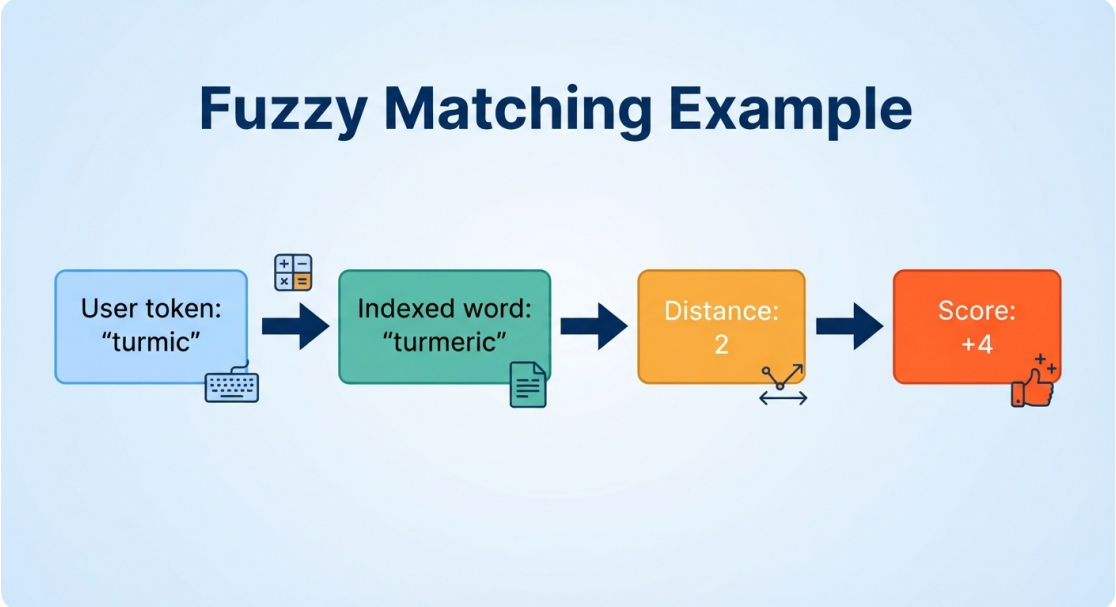
19. Levenshtein Fuzzy Retrieval

Oracle implements Levenshtein distance for approximate string comparison.

19.1 Fuzzy Matching Rules

Distance	Score
0 (exact)	+10
1	+7
2	+4
>2	0

19.2 Fuzzy Matching Example



19.3 Fuzzy Matching Caveat

Fuzzy similarity is not semantic similarity.

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20. Candidate Generation

Candidate generation aggregates all matches from exact matching, title/excerpt matching, token-level matching, and fuzzy matching. Candidates are then passed to category weighting, type-specific boosting, and recommendation influence.

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21. Category Weighting

Category weighting is one of Oracle's domain-aware ranking mechanisms. After exact, token-level, and fuzzy contributions have been calculated, Oracle multiplies the hybrid score by a category-specific weight. This allows different knowledge categories to influence ranking according to domain semantics.

Category weighting is not a clinical importance metric. It is an engineering parameter designed to improve retrieval usefulness across heterogeneous health knowledge.

21.1 Purpose of Category Weighting

Category weighting serves several purposes:

1. Domain-aware ranking — Different health-information categories have different retrieval characteristics.

2. Cross-domain balancing — Conditions, herbs, symptoms, medications, interactions, and protocols may all appear in the same result set.

3. Typed knowledge prioritization — Certain categories (e.g., saved items) may be more relevant to the user's current context.

4. Improved retrieval diversity — Category weighting helps ensure that relevant objects from multiple categories appear in the result set.

21.2 Category Weight Table (Current Implementation)

Category	Weight	Description
Herbs	**1.5**	Herbal profiles often contain rich content and synonyms
Symptoms	**1.3**	Symptom categories frequently match user queries
Medications	**1.2**	Pharmaceutical knowledge is structured but narrower
Interactions	**1.4**	Interaction records are highly relevant for safety
Traditions	**1.3**	Traditional medicine concepts often match multi-concept queries
Protocols	**1.2**	Protocols contain structured steps and ingredients
Wellness	**1.1**	User-generated records are contextually relevant
Saved Items	**1.8**	Saved items are highly relevant to user intent

These values are implementation constants, not evidence grades.

21.3 Category Weighting Formula

Let:

- S_{hybrid} = hybrid lexical/fuzzy score
- W_{category} = category weight

Then:

text

S_weighted = S_hybrid × W_category

21.4 Category Weighting Example

Suppose:

- Hybrid score = 50
- Category = "herb"
- Weight = 1.5

Then:

text

S_weighted = 50 × 1.5 = 75

21.5 Category Weighting Caveats

Category weighting does **not** imply clinical importance, evidence quality, treatment priority, or diagnostic relevance. It is purely a ranking mechanism.

---

22. Type-Specific Boosting

Type-specific boosting is an additive ranking mechanism applied after category weighting. It allows Oracle to adjust ranking based on the type of the knowledge object.

22.1 Purpose of Type-Specific Boosting

Type-specific boosting serves several purposes:

1. Typed knowledge prioritization — Certain types may be more relevant to user intent.

2. Cross-category balancing — Boosting helps ensure that relevant objects from multiple types appear in the result set.

3. User-context alignment — Saved items and wellness records may be more relevant to the user's current context.

22.2 Type-Specific Boost Table

Type	Boost	Description
Condition	+10	Conditions often match symptom queries
Herb	+8	Herbs frequently match remedy queries
Symptom	+6	Symptoms often match natural-language queries
Medication	+5	Medications match pharmaceutical queries
Interaction	+7	Interactions are safety-critical
Tradition	+4	Traditional concepts match multi-concept queries
Protocol	+5	Protocols match structured queries
Wellness	+3	Wellness records match user history
Saved	+12	Saved items are highly relevant

These values are implementation constants.

22.3 Type Boosting Formula

Let:

- S_{weighted} = category-weighted score
- B_{type} = type-specific boost

Then:

text

S_boosted = S_weighted + B_type

22.4 Type Boosting Example

Suppose:

- Weighted score = 75
- Type = "saved"
- Boost = +12

Then:

text

S_boosted = 75 + 12 = 87

22.5 Type Boosting Caveats

Type boosting does **not** imply clinical importance, evidence quality, treatment priority, or diagnostic relevance. It is purely a ranking mechanism.

---

23. Ranking and Scoring

Ranking is the process of ordering candidate results according to their final score. Oracle's ranking framework combines exact matching, title/excerpt matching, token-level matching, fuzzy matching, category weighting, type-specific boosting, and recommendation influence.

23.1 Conceptual Ranking Formula

The conceptual ranking formula is:

text

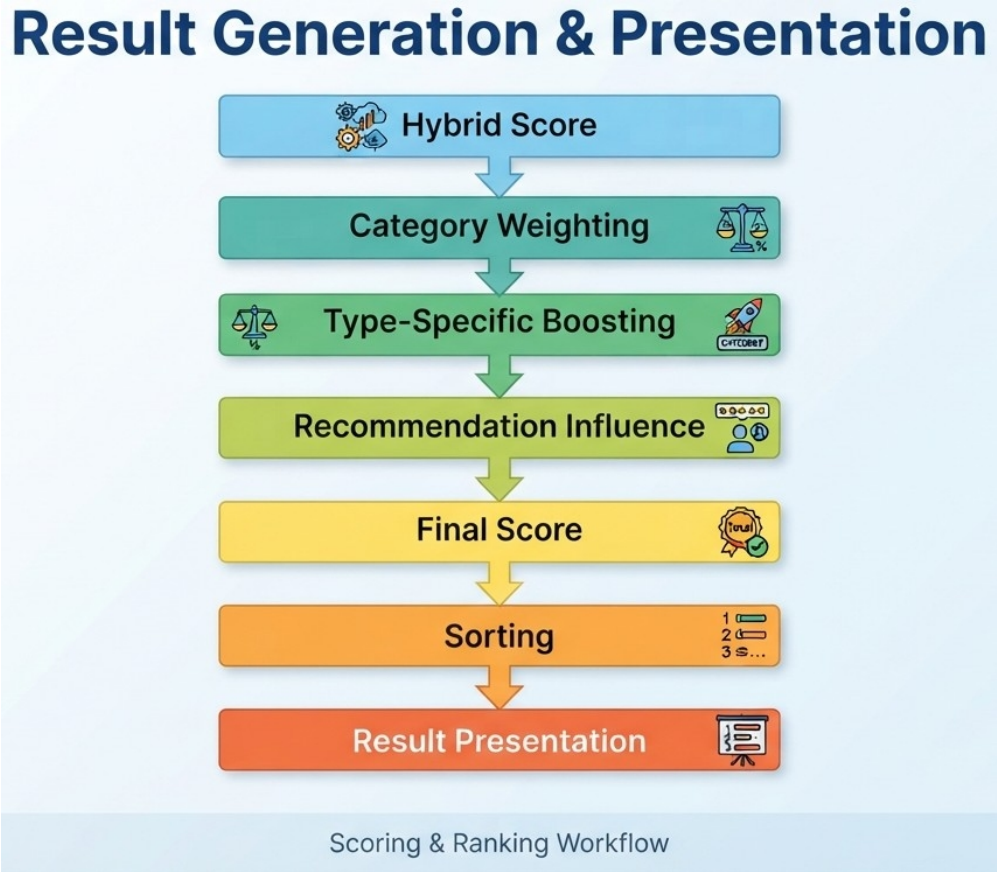
S = (S_exact + S_token + S_fuzzy) × W_category + B_type + B_recommendation

Where:

- S_{exact} = exact/content matching contribution
- S_{token} = token-level matching contribution
- S_{fuzzy} = fuzzy matching contribution
- W_{category} = category weight
- B_{type} = type-specific boost
- B_{recommendation} = optional recommendation influence

This formula is conceptual; the actual implementation contains explicit constants and conditional pathways.

23.2 Ranking Pipeline Diagram



23.3 Ranking Modes

Oracle supports multiple ranking modes:

- **Relevance (default)**
- **Date**
- **Confidence**
- **Category**

Relevance mode sorts by descending score.

23.4 Ranking Table Example

Object	Hybrid Score	Weighted	Boosted	Final Score
Herb A	50	75	83	83
Symptom B	40	52	58	58
Condition C	45	58.5	68.5	68.5

24. Algorithmic Confidence

Oracle displays percentage-style match values to users. These values are derived from the internal score and a calculated maximum possible score.

24.1 Confidence Formula

Let:

- S = final score
- S_{max} = maximum possible score

Then:

text

C = min(100, round(S / S_max × 90 + 5))

24.2 Confidence Interpretation

Algorithmic confidence is **not** probability of correctness, probability of clinical relevance, probability of user satisfaction, evidence quality, diagnostic probability, or treatment probability. It is a normalized match score.

24.3 Confidence Table Example

Score	Max Score	Confidence
80	100	77%
50	100	50%
20	100	23%

24.4 Confidence Caveats

Confidence values are algorithmic, not calibrated, require validation, and should not be interpreted as probabilities.

---

25. NHOS Matrix Engine

The **NHOS Matrix Engine™** is Oracle's multi-concept retrieval subsystem. It is activated when a user enters a query containing more than one concept separated by delimiters such as commas, semicolons, pipes, bullets, or line breaks.

The Matrix Engine is not a semantic model. It is a **multi-concept lexical engine** designed to identify which indexed knowledge objects intersect with the set of concepts represented by the query.

This subsystem is essential for symptom clusters, compound health queries, multi-factor exploration, cross-domain discovery, structured protocol queries, and traditional medicine multi-concept queries. The Matrix Engine is one of Oracle's most distinctive architectural contributions.

Part III: Matrix & Recommendation Intelligence

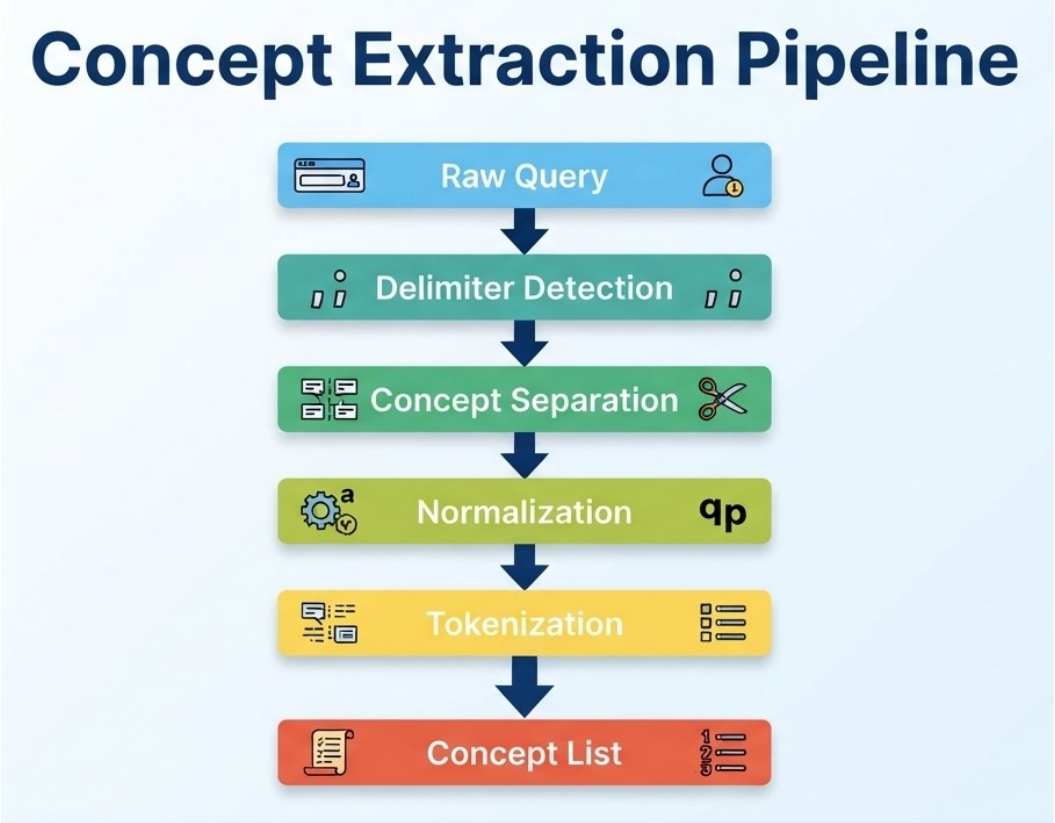
26. Multi-Concept Query Parsing

26.1 Delimiter Rules

Oracle recognizes the following delimiters:

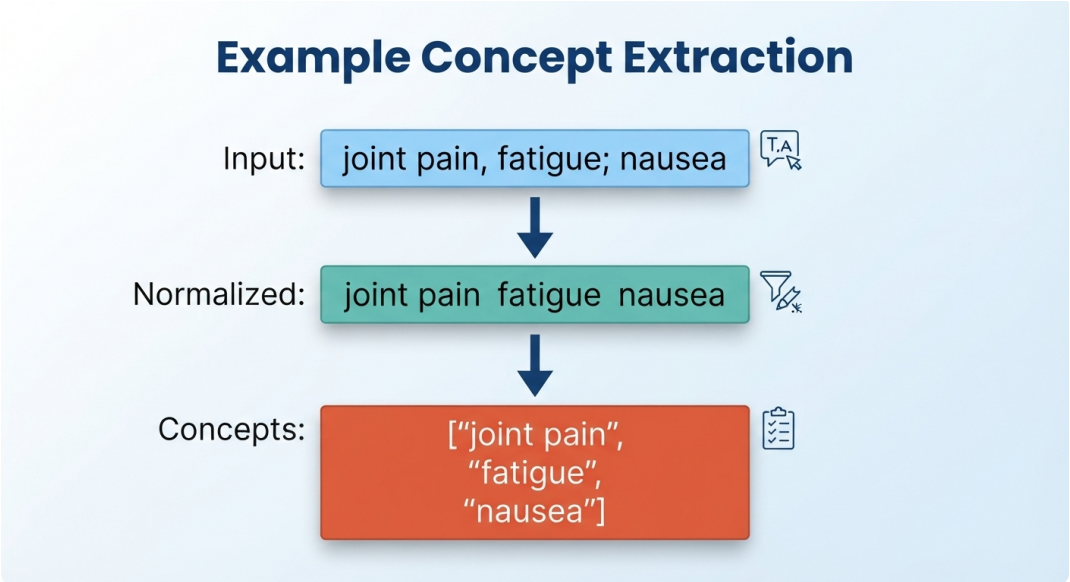
Delimiter	Example
Comma	"fatigue, nausea, headache"
Semicolon	"fatigue; nausea; headache"
Pipe	"fatigue | nausea | headache"
Bullet	"• fatigue • nausea • headache"
Line break	"fatigue\nnausea\nheadache"

26.2 Concept Extraction Pipeline



Concept Extraction Workflow

26.3 Example Concept Extraction



26.4 Concept Extraction Table

Input	Concepts
"fatigue, nausea"	["fatigue", "nausea"]
**"headache	dizziness"**	["headache", "dizziness"]
"• anxiety • poor sleep • irritability"	["anxiety", "poor sleep", "irritability"]

27. Matrix Matching

27.1 Matrix Matching Logic

For each concept:

1. Normalize concept

2. Tokenize concept

3. Compare tokens against title, excerpt, content, and metadata

4. If any token matches → concept is considered matched

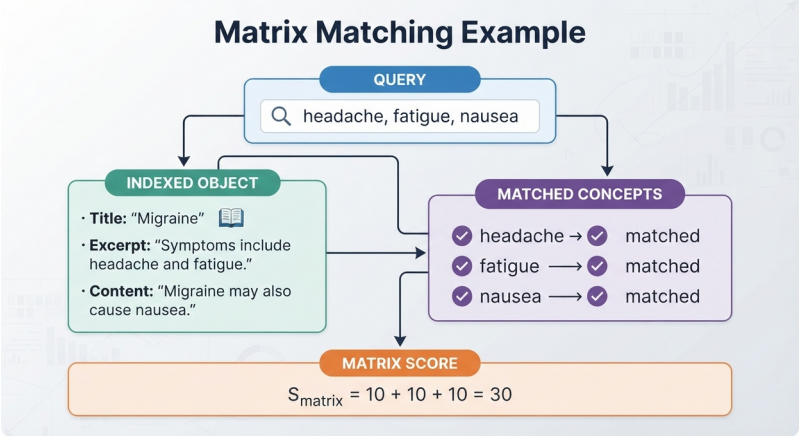
5. Record matched concept

6. Accumulate Matrix score

27.2 Matrix Matching Score

The current implementation assigns **+10 points per matched concept**.

27.3 Matrix Matching Example



27.4 Matrix Matching Caveats

Matrix matching is lexical, not semantic. It does not infer meaning, expand synonyms, interpret medical relationships, or perform concept weighting. It is purely a concept-coverage mechanism.

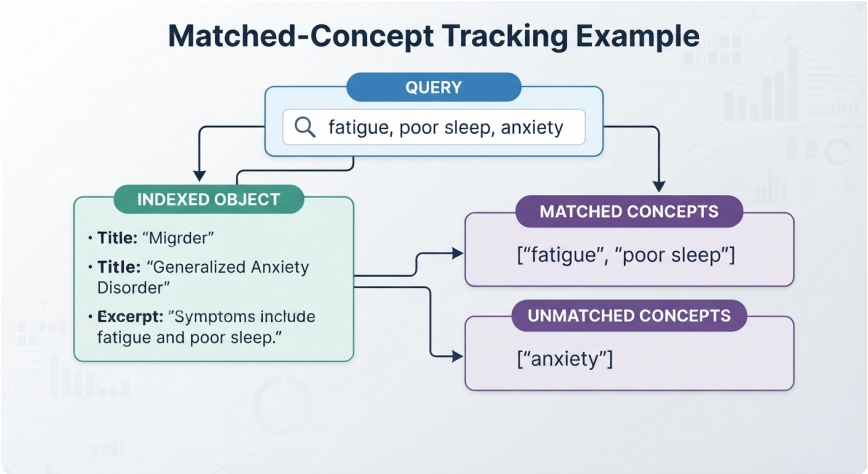
---

28. Matched-Concept Tracking

28.1 Purpose of Matched-Concept Tracking

Matched-concept tracking allows Oracle to show users which concepts were matched, support explainable retrieval, support clinical mode transparency, support debugging and validation, and support Matrix evaluation metrics.

28.2 Matched-Concept Tracking Example



28.3 Matched-Concept Indicator Table

Concept	Status
fatigue	✓ matched
poor sleep	✓ matched
anxiety	✗ not matched

28.4 Explainability Benefit

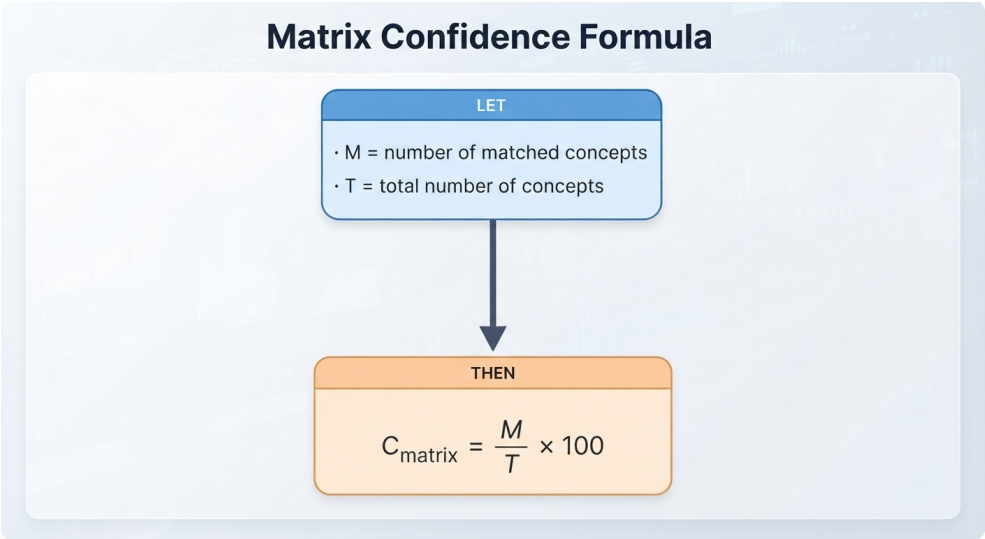
Matched-concept tracking allows Oracle to display matched tokens, matched concepts, concept coverage, partial matches, and missing concepts. This supports explainable retrieval.

---

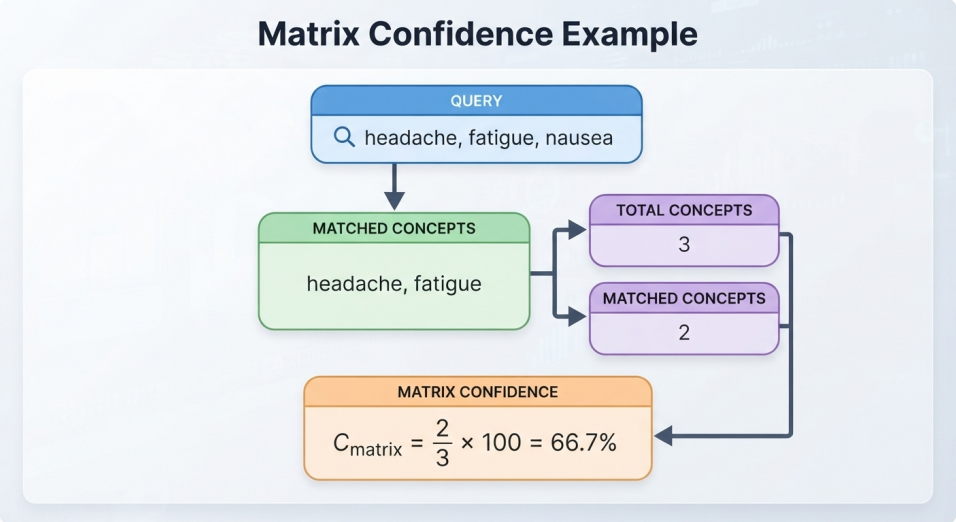
29. Matrix Confidence / Coverage

Matrix confidence is a concept-coverage metric. It measures how many concepts were matched relative to the total number of concepts.

29.1 Matrix Confidence Formula



29.2 Matrix Confidence Example



29.3 Matrix Confidence Table

Matched	Total	Coverage
3	3	100%
2	3	66.7%
1	3	33.3%
0	3	0%

29.4 Matrix Confidence Caveats

Matrix confidence is not a probability, not evidence quality, not clinical relevance, not diagnostic probability, and not treatment probability. It is purely a concept-coverage metric.

---

30. Matrix Engine vs. Hybrid Retrieval

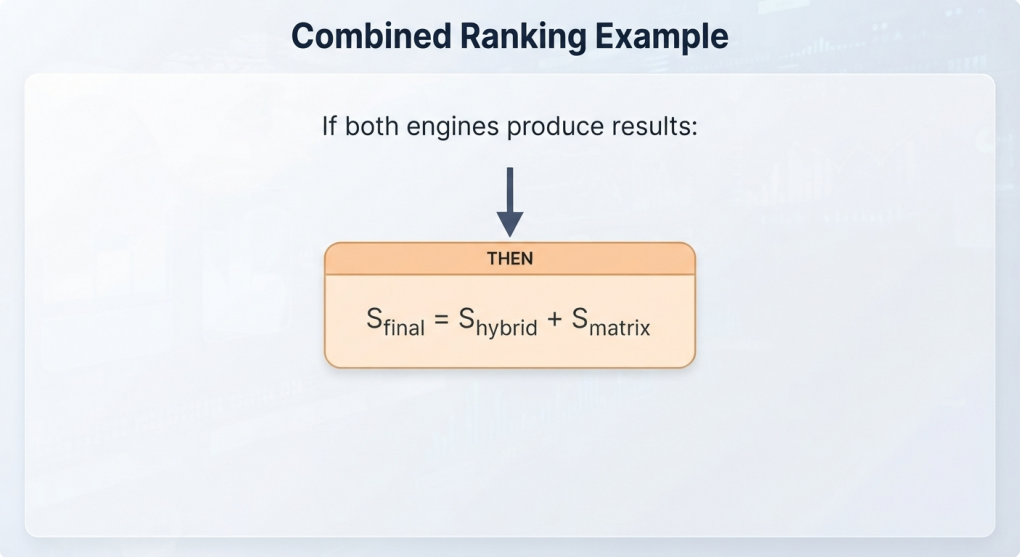
Feature	Hybrid Retrieval	Matrix Engine
Query type	single concept	multi-concept
Matching	lexical + fuzzy	lexical only
Ranking	weighted + boosted	concept coverage

Feature	Hybrid Retrieval	Matrix Engine
Confidence	normalized score	coverage percentage
Explainability	partial	full concept tracking
Use case	general search	multi-concept search

30.2 Combined Retrieval Behavior

Oracle uses the Matrix Engine for multi-concept queries and Hybrid Retrieval for single-concept queries, with combined ranking when both produce results.

30.3 Combined Ranking Example



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31. Matrix Engine Research Potential

31.1 Research Opportunities

Matrix retrieval enables research into concept coverage, false-positive intersections, missing-concept behavior, ranking among partial matches, synonym sensitivity, spelling sensitivity, and multi-concept scaling.

31.2 Multi-Concept Scaling

As concept count increases, coverage becomes more granular, partial matches become more common, ranking becomes more complex, and explainability becomes more important.

31.3 Matrix Engine Limitations

Matrix Engine limitations include lexical dependence, no semantic expansion, no synonym expansion, no concept weighting, and no probabilistic modeling.

---

32. NHOS Recommendations Engine™

The **NHOS Recommendations Engine™** is Oracle's local contextual discovery subsystem. It is designed to provide adaptive suggestions based on recent interaction history, recurring categories, recurring query terms, selected items, and contextual heuristics.

Unlike machine-learning recommenders, the NHOS Recommendations Engine is deterministic in its logic, local-first, privacy-oriented, non-probabilistic, non-predictive, and non-centralized. It does **not** use embeddings, vector similarity, collaborative filtering, or neural models. It is a **local contextual heuristic engine**.

---

33. Local Interaction History

33.1 Interaction History Structure

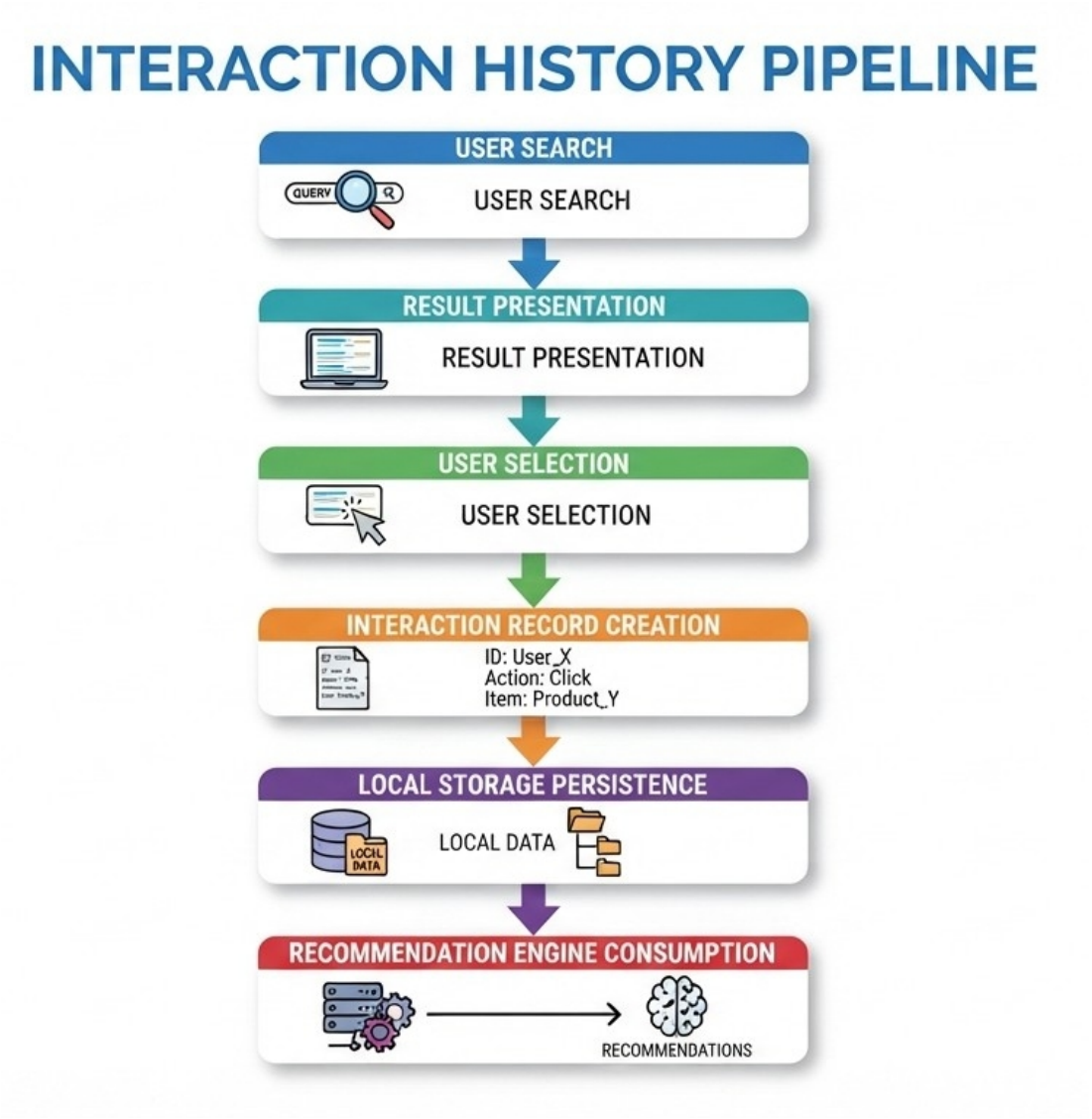
Each interaction record may contain:

Field	Description
query	The user's search query
resultCount	Number of results returned
selectedItem	The item the user clicked
timestamp	Time of interaction
category	Category of selected item

33.2 Interaction History Capacity

Oracle retains **up to 100 records**, with the **most recent 20 records** used for recommendation generation. Older records are discarded.

33.3 Interaction History Pipeline



text

User Search ↓Result Presentation ↓User Selection ↓Interaction Record Creation ↓Local Storage Persistence ↓Recommendation Engine Consumption

33.4 Interaction History Example

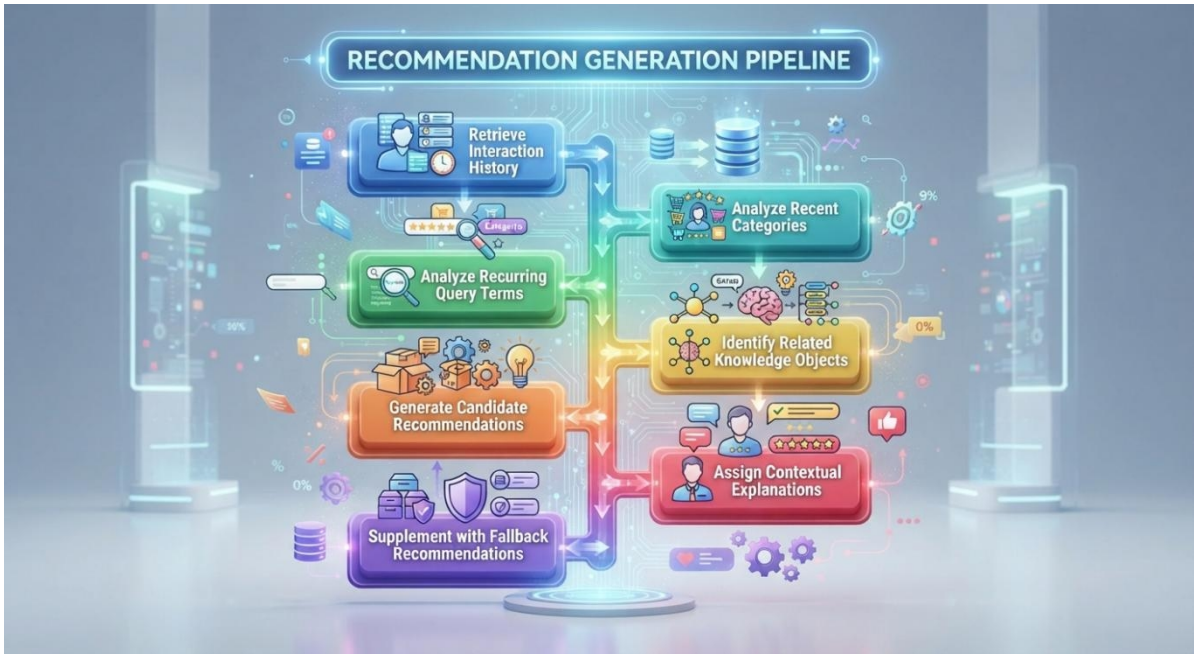
json

{ "query": "joint pain", "resultCount": 42, "selectedItem": "Turmeric", "timestamp": "2026-08-27T09:12:00Z", "category": "herb"}

---

34. Recommendation Generation

34.1 Recommendation Generation Pipeline



text

Retrieve Interaction History ↓Analyze Recent Categories ↓Analyze Recurring Query Terms ↓Identify Related Knowledge Objects ↓Generate Candidate Recommendations ↓Assign Contextual Explanations ↓Supplement with Fallback Recommendations

34.2 Category Interest Detection

The recommendation engine identifies categories that appear frequently in recent interactions. If the user repeatedly selects herbs, Oracle may recommend related herbs, herb interactions, or herb protocols.

34.3 Query-Term Recurrence Detection

The engine identifies recurring query terms. If the user repeatedly searches for "fatigue," Oracle may recommend fatigue-related herbs, fatigue-related conditions, or fatigue-related protocols.

34.4 Candidate Recommendation Selection

Candidate recommendations are selected based on category interest, query-term recurrence, related knowledge objects, and deterministic heuristics. Some parts of the implementation include randomized selection among candidates.

34.5 Contextual Explanation Generation

Oracle generates contextual explanations such as:

- "You've recently viewed several herbs."
- "You've searched for fatigue multiple times."
- "You selected a condition related to your last query."

34.6 Fallback Recommendations

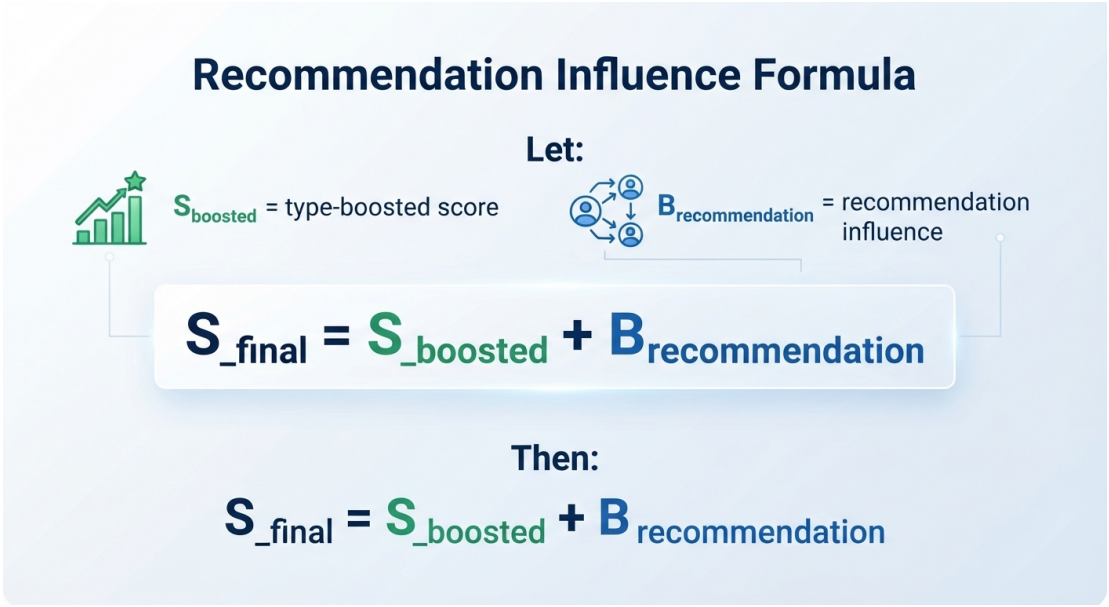
If contextual recommendations are insufficient, Oracle supplements them with popular herbs, common symptoms, frequently accessed conditions, or general wellness suggestions.

---

35. Recommendation Influence on Retrieval

When NHOS Recommendations mode is active, recommendation-derived information can influence ranking.

35.1 Recommendation Influence Formula



Let:

- S_{boosted} = type-boosted score
- B_{recommendation} = recommendation influence

Then:

text

S_final = S_boosted + B_recommendation

35.2 Recommendation Influence Weight

The current implementation incorporates **30% of the recommendation score** into the hybrid retrieval score.

35.3 Recommendation Influence Caveats

Recommendation influence is not a probability, not a prediction, not a machine-learning model, and not a clinical relevance metric. It is a contextual ranking adjustment.

Part IV: Application/Interaction Architecture

36. Local Search Analytics

36.1 Analytics Data Structure

Analytics records may include:

Field	Description
query	Search query
resultCount	Number of results
timestamp	Time of search
activeFilter	Filter used
clinicalMode	Whether clinical mode was active
matrixMode	Whether Matrix mode was active
recommendationMode	Whether recommendations were active

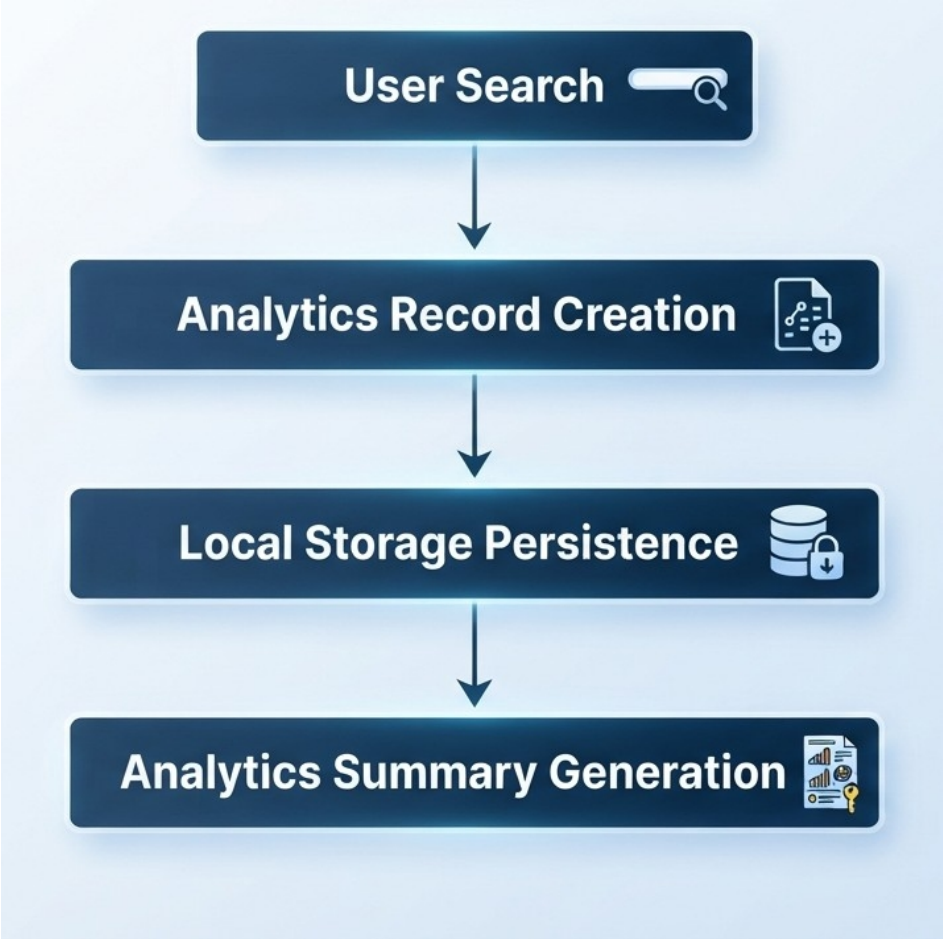
36.2 Analytics Capacity

Oracle retains **up to 100 analytics records**.

36.3 Analytics Summary Metrics

Oracle derives total searches, top category, popular queries, average result count, recent search trends, and category distribution.

36.4 Analytics Pipeline



36.5 Analytics Caveats

Local analytics do **not** imply absence of network communication, do **not** imply complete privacy, and require separate privacy evaluation.

---

37. Autocomplete Architecture

37.1 Autocomplete Matching Stages

Autocomplete supports:

1. Title-prefix matching

2. Word-level matching

3. Token-level matching

4. Levenshtein fuzzy matching

37.2 Autocomplete Pipeline

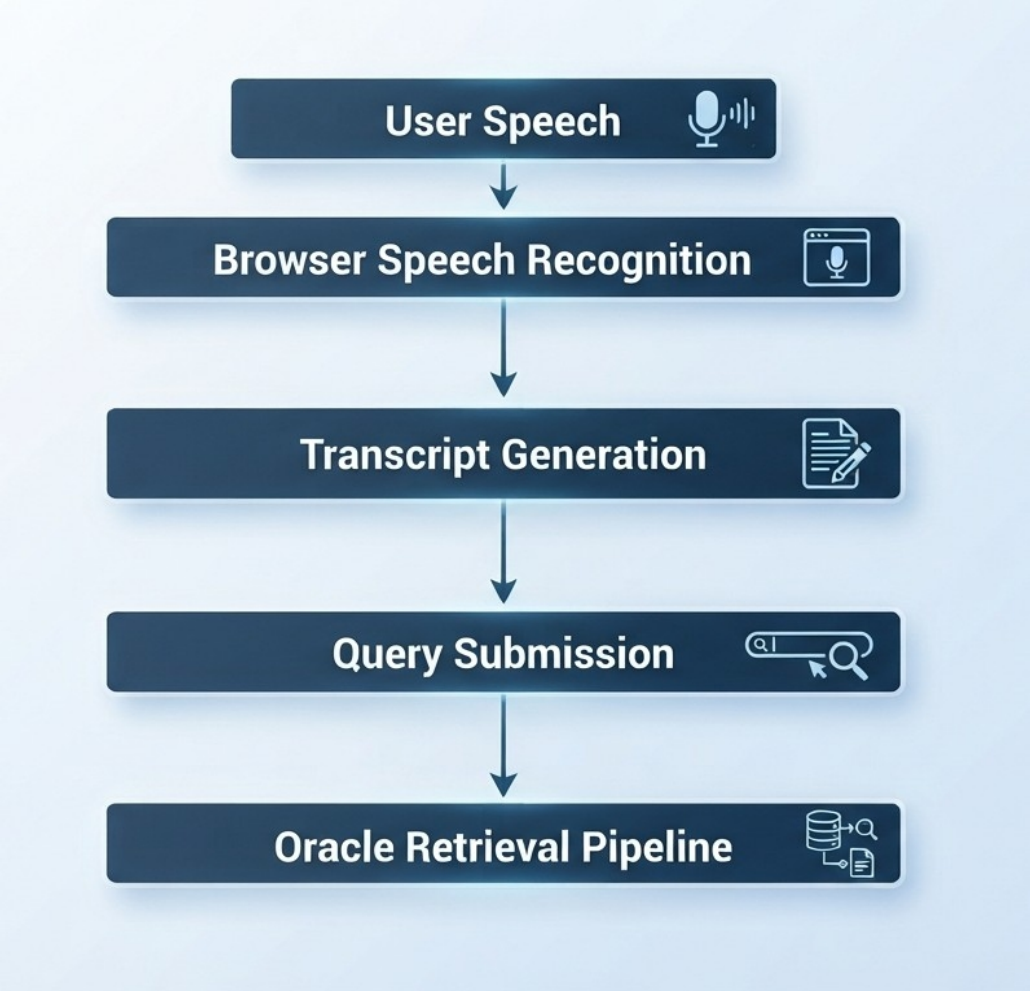
37.3 Autocomplete Limitations

Autocomplete is not semantic, does not infer meaning, does not expand synonyms, and is purely lexical.

---

38. Voice Search

38.1 Voice Search Pipeline



text

User Speech ↓Browser Speech Recognition ↓Transcript Generation ↓Query Submission ↓Oracle Retrieval Pipeline

38.2 Voice Search Caveats

Voice search depends on browser support, device support, and speech-service implementation, and may vary across platforms. Oracle does not implement speech recognition itself.

---

39. Filtering and Sorting

Oracle provides multiple filtering mechanisms. The current interface exposes categories including conditions, herbs, symptoms, medications, interactions,

traditions, protocols, wellness, and saved items. It also exposes advanced filtering and sorting options including evidence level, date range, relevance, date, confidence, and category.

These controls provide users with explicit mechanisms for narrowing or reorganizing results. They also create additional dimensions for future usability research.

---

40. Clinical Mode

Oracle contains a Clinical Mode that changes the interface and enables evidence-level filtering behavior. For certain result types, the current implementation derives a displayed evidence label from the calculated confidence value: High, Moderate, or Low. The thresholds are implementation-based.

This feature requires particularly careful interpretation. The displayed evidence label should **not** be treated as a validated assessment of clinical evidence quality merely because it appears under a "Clinical" interface mode. The current implementation uses algorithmic thresholds. A future evidence-model validation would require independent evidence grading, source provenance, explicit criteria, and expert review. For this reason, this paper treats Clinical Mode as an **implemented interface and filtering mechanism**, not as evidence that Oracle performs clinically validated evidence appraisal.

---

41. Knowledge Discovery and Application Orchestration

Oracle's role extends beyond retrieval. When a user selects a result, the implementation can route the user toward corresponding NHOS functionality.

Examples include:

- conditions → remedy-related functionality;
- herbs → Herbs Library;
- symptoms → Symptom Checker;
- medications/interactions → Interaction Checker;
- traditions → Traditional Medicine functionality;
- protocols → protocol functionality;
- wellness → wellness functionality;

• saved items → saved/remedy functionality.

Oracle therefore operates as an **orchestration layer for knowledge discovery**.

The architecture can be represented as:

text

Search → Discover → Preview → Classify → Open specialized NHOS tool

This is an important architectural distinction. Oracle does not need to contain every downstream health-information function itself. Instead, it can act as a common discovery gateway into a modular health-information ecosystem.

---

42. Saved Knowledge

Oracle provides a saved items mechanism where users can bookmark or save specific knowledge objects. Saved items receive a high category weight (1.8), reflecting their potential relevance to the user's current context. This saved state is persisted locally and used by the recommendation engine to improve contextual suggestions.

---

43. Export Architecture

Oracle provides multiple result-export pathways. The current implementation exposes CSV, PDF, JSON, XML, and DOC-compatible export. The export functionality includes engine/version metadata and result information.

These capabilities are engineering features rather than core research contributions. Nevertheless, they may become important for reproducibility because exported search results can potentially support test-case documentation, human relevance review, research records, audit trails, comparison studies, and reproducible evaluation. Future versions should consider embedding structured benchmark metadata into exports.

---

44. Sharing

Oracle provides sharing capabilities that allow users to share search results. The sharing functionality may involve network communication and should be evaluated as part of the privacy and network audit. The sharing feature is disabled in offline mode.

---

45. Local-First Architecture

The NHOS Oracle Matrix Search Engine™ is designed around a **local-first architectural principle**. This principle asserts that useful health-information retrieval and contextual discovery can occur locally where functionally appropriate, reducing unnecessary transmission of queries, search history, interaction records, local knowledge, and user-generated wellness data.

Local-first is not a privacy certification. It is an architectural strategy that may reduce data movement.

45.1 Definition of Local-First

Local-first systems prioritize local execution, local persistence, offline capability, user control, and minimized centralized dependency.

Local-first does **not** imply complete privacy, complete security, absence of network communication, resistance to device compromise, resistance to malicious extensions, secure deletion, or encryption at rest.

45.2 Local-First Architecture Diagram

text

User Query ↓Local Oracle Engine ↓Local Knowledge Index ↓Local Retrieval & Ranking ↓Local Recommendations ↓Local Analytics ↓Local Result Presentation

Remote services are only used when knowledge assets are not yet cached, the user explicitly requests cloud-based features, NHOS.health resources are accessed, or updates are fetched.

45.3 Local-First Benefits

Local-first architecture provides reduced latency, offline capability, user control over local data, reduced dependency on centralized services, and potential reduction in unnecessary data transmission.

45.4 Local-First Limitations

Local-first architecture introduces reproducibility challenges, device-specific behavior, browser-specific behavior, local storage variability, and offline caching complexity. These limitations require controlled validation.

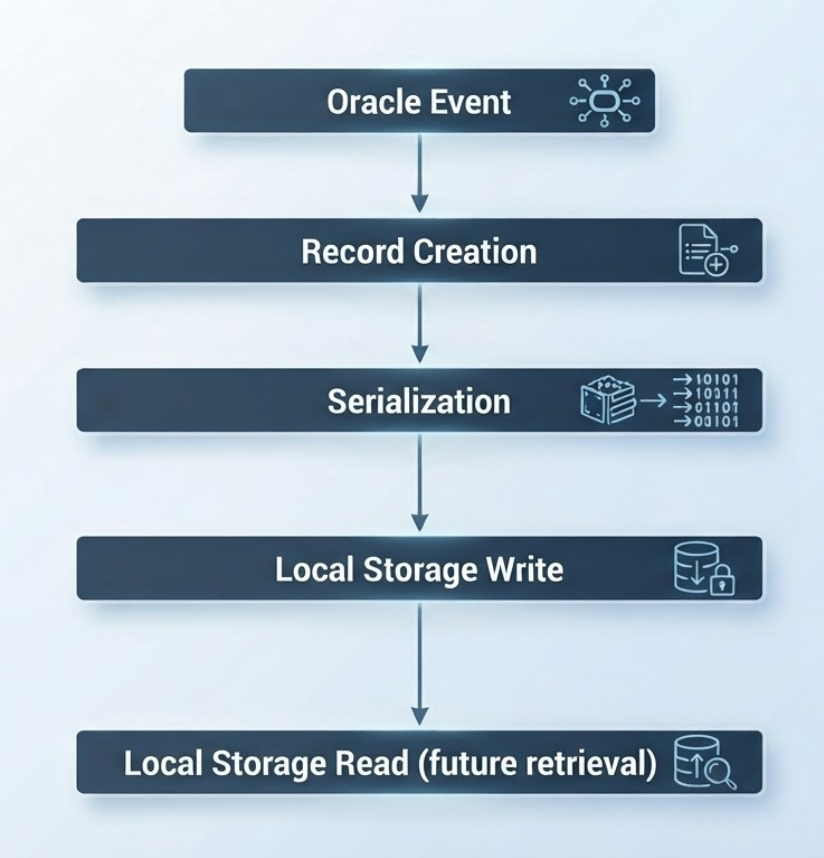
Part V: Local-First Infrastructure

46. Local Persistence

46.1 Local Persistence Mechanisms

Oracle uses localStorage, sessionStorage, cached assets, and browser-level persistence. These mechanisms depend on browser implementation, device behavior, user settings, privacy mode, and storage availability.

46.2 Local Persistence Pipeline



text

Oracle Event ↓Record Creation ↓Serialization ↓Local Storage Write ↓Local Storage Read (future retrieval)

46.3 Local Persistence Caveats

Local persistence may be cleared by the user, browser settings, privacy mode, or device cleanup, and may vary across browsers and devices. Local persistence is not guaranteed.

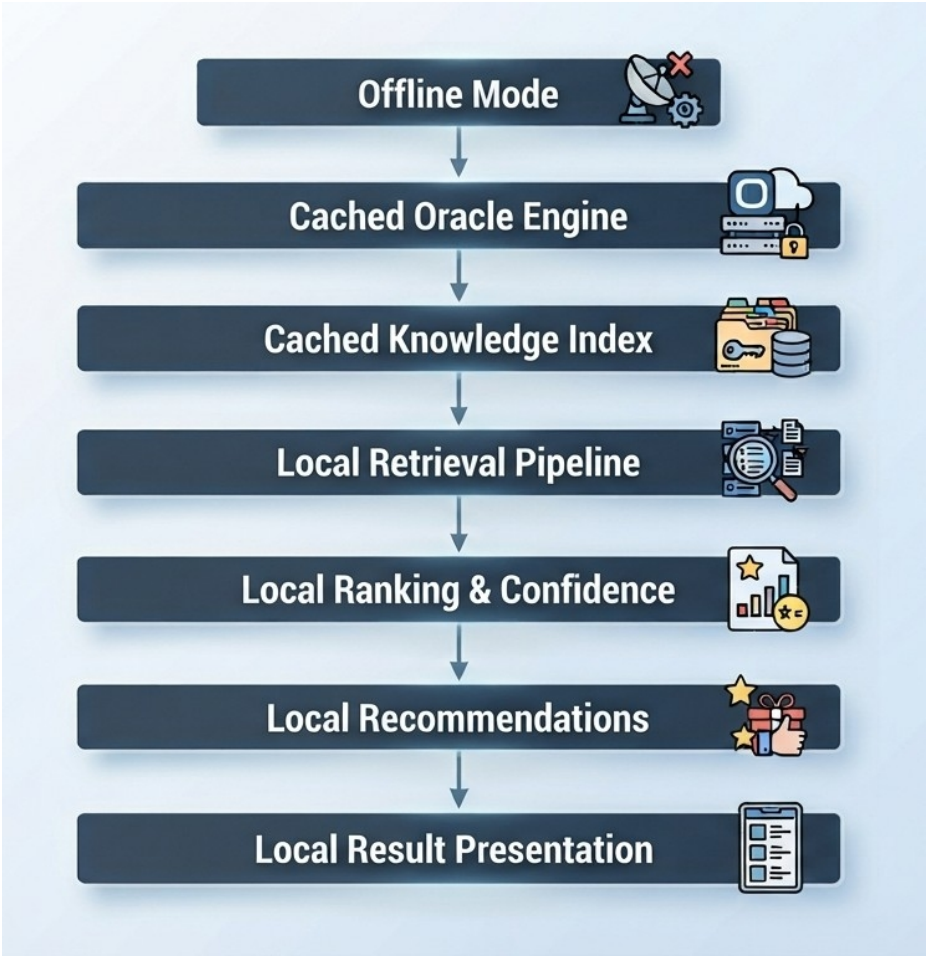
---

47. Offline Architecture

47.1 Offline Capability Requirements

Offline capability requires cached application assets, cached knowledge assets, local storage availability, and browser support for offline caching.

47.2 Offline Architecture Diagram



text

Offline Mode ↓Cached Oracle Engine ↓Cached Knowledge Index ↓Local Retrieval Pipeline ↓Local Ranking & Confidence ↓Local Recommendations ↓Local Result Presentation

47.3 Offline Capability Classification

Feature	Offline Status
Hybrid Retrieval	Fully operational
Matrix Engine	Fully operational
Recommendations	Fully operational
Local Analytics	Fully operational
Saved Items	Fully operational
Export	Partially operational

Feature	Offline Status
Sharing	Requires connectivity
Voice Search	Requires connectivity
Knowledge Updates	Requires connectivity

47.4 Offline Testing Requirements

Offline validation must test first-load behavior, cached behavior, local knowledge availability, browser restart behavior, network-disabled retrieval, network-disabled recommendations, network-disabled analytics, network-disabled export, and network-disabled sharing.

47.5 Offline Caveats

Offline capability depends on browser caching, device storage, and user settings, and may vary across platforms. Offline capability is not guaranteed.

---

48. Privacy Model

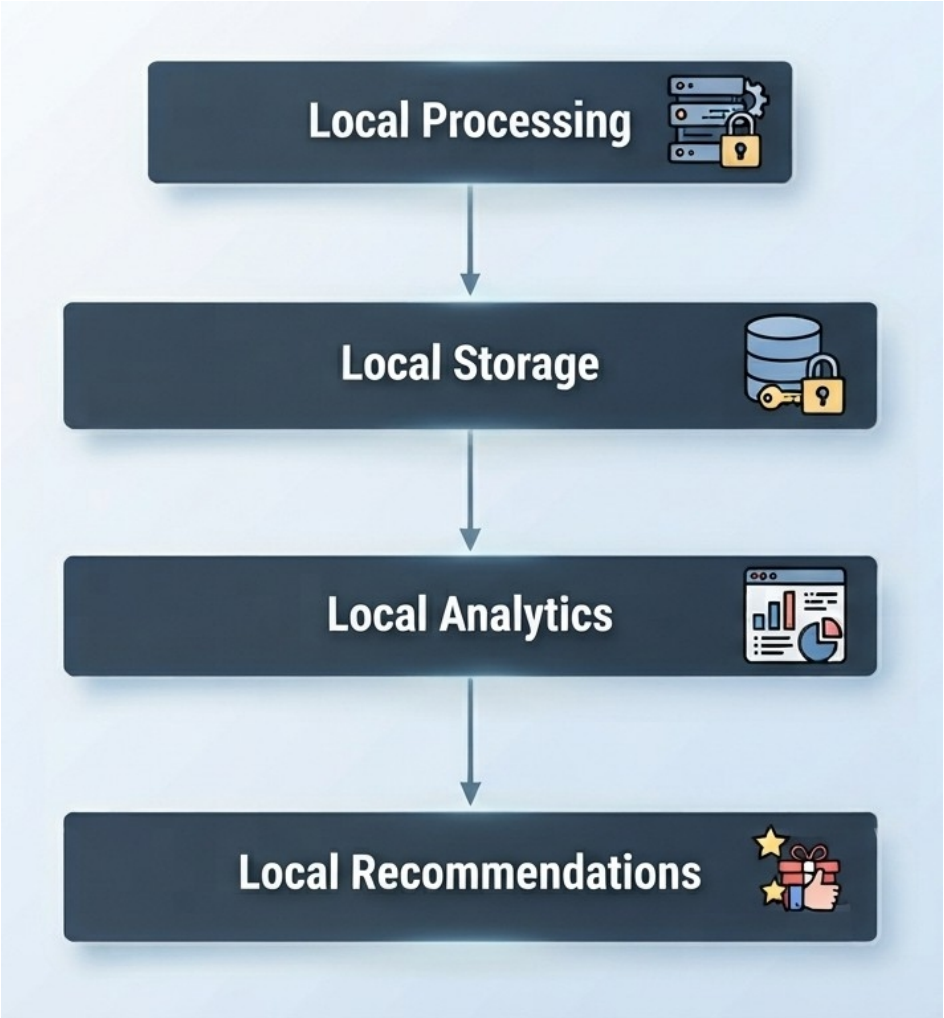
48.1 Privacy Model Principles

Oracle's privacy model emphasizes local processing where appropriate, local storage of interaction history, local recommendation generation, local analytics, and local-first retrieval.

48.2 Privacy Model Caveats

Local-first architecture does **not** imply complete privacy, complete security, absence of network communication, resistance to device compromise, resistance to malicious extensions, secure deletion, or encryption at rest.

48.3 Privacy Model Diagram



text

Local Processing ↓Local Storage ↓Local Analytics ↓Local Recommendations

Remote communication occurs only when knowledge assets are fetched, updates are retrieved, or NHOS.health resources are accessed.

48.4 Privacy Evaluation Requirements

Privacy evaluation must audit network requests, destinations, payloads, browser storage, local persistence, third-party resources, export behavior, and sharing behavior.

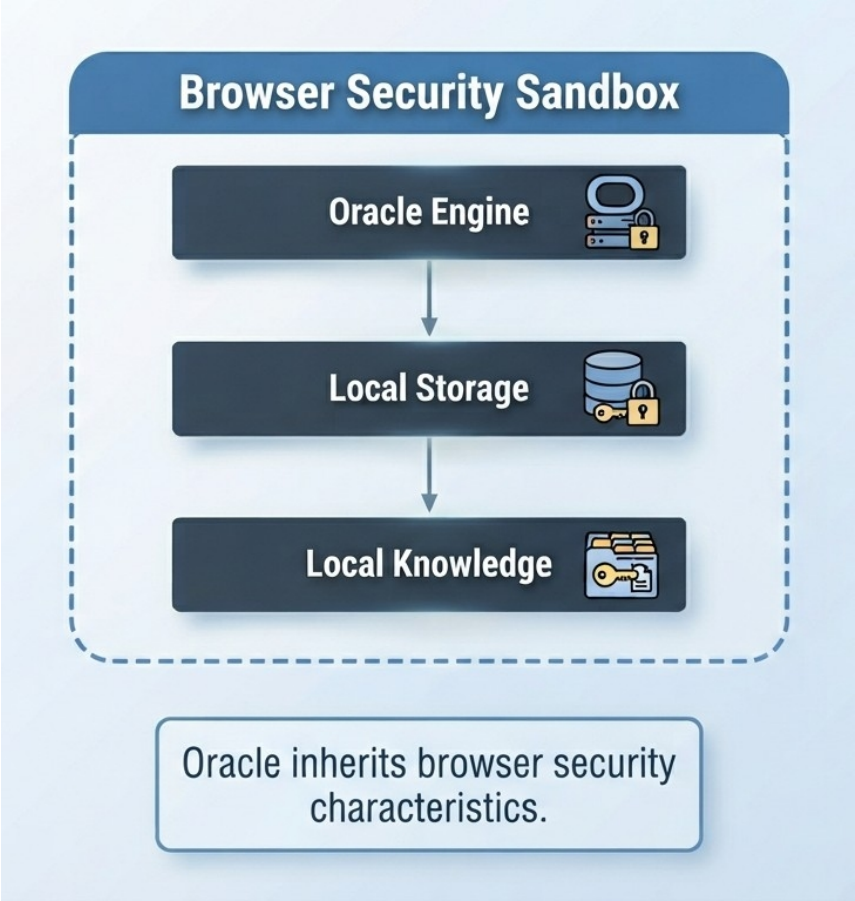
---

49. Security Boundaries

49.1 Security Boundary Considerations

Security evaluation must consider unauthorized local access, malicious browser extensions, cross-site scripting, injected scripts, local storage inspection, export-based data leakage, browser synchronization, third-party APIs, accidental sharing, and cross-application exposure.

49.2 Security Boundary Diagram



text

Browser Security Sandbox ↓Oracle Engine ↓Local Storage ↓Local Knowledge

Oracle inherits browser security characteristics.

49.3 Security Boundary Caveats

Oracle does **not** guarantee resistance to malicious extensions, resistance to device compromise, secure deletion, encryption at rest, or complete isolation.

---

50. Data Lifecycle

50.1 Data Lifecycle Stages

text

Data Creation ↓Local Storage ↓Local Use ↓Local Update ↓Local Deletion

50.2 Data Creation

Data is created when the user performs a search, selects a result, saves an item, or interacts with Oracle.

50.3 Data Storage

Data is stored in localStorage, sessionStorage, and cached assets.

50.4 Data Use

Data is used for recommendations, analytics, saved items, and offline capability.

50.5 Data Update

Data is updated when new interactions occur, new analytics are generated, or saved items are modified.

50.6 Data Deletion

Data may be deleted by user action, browser settings, privacy mode, or device cleanup.

---

51. Implementation Status

As of Version 6.3, Oracle demonstrably implements:

Retrieval

- exact/content matching;
- title/excerpt weighting;
- token matching;
- fuzzy Levenshtein matching;
- category weighting;
- type-specific boosts;
- result ranking.

Matrix

- multi-concept query parsing;
- concept matching;
- matched-token reporting;
- Matrix confidence calculation.

Contextual intelligence

- local recommendation history;
- recurring category analysis;
- recurring query-term analysis;
- contextual suggestions;
- recommendation influence on ranking.

User interaction

- autocomplete;
- voice input where browser-supported;
- filtering;
- sorting;
- local analytics;
- visual analytics;
- preview;
- saving;
- export;
- sharing;
- specialized-tool navigation.

These capabilities are supported by the implementation.

---

52. What Has Not Yet Been Demonstrated

The following should **not** be presented as established scientific findings:

- superior retrieval performance;
- superior ranking quality;
- clinical effectiveness;

- diagnostic accuracy;
- recommendation effectiveness;
- calibrated confidence;
- reduced health-information errors;
- improved health outcomes;
- superiority to semantic/vector retrieval;
- superiority to BM25;
- privacy superiority;
- security superiority;
- statistically significant user benefit.

These are research hypotheses or validation targets.

Part VI: Evidence Discipline & Safety

53. Explicit Non-Claims

For scientific clarity, NHOS Oracle does not claim in this paper to be:

A semantic search engine

The current source does not demonstrate an embedding model, vector database, transformer-based semantic retrieval mechanism, cosine-similarity retrieval, or equivalent conventional semantic-search infrastructure.

A machine-learning recommender

The current recommendation mechanism uses local interaction history and heuristics and includes randomized selection in parts of its current implementation.

A clinically validated decision-support system

Oracle retrieves and organizes health information. Retrieval capability does not establish clinical validity.

A validated evidence-grading system

Clinical-mode labels currently derive from algorithmic thresholds rather than independently validated evidence appraisal.

A probability-calibrated confidence model

Displayed confidence percentages are internally calculated scores.

These boundaries are deliberate.

---

54. Known Technical Limitations

54.1 Lexical dependence

Oracle's current retrieval system depends heavily on textual representation. It may fail when two concepts are semantically related but lexically dissimilar.

54.2 Fuzzy-match limitations

Levenshtein distance can identify spelling similarity but does not establish semantic similarity.

54.3 Weighting assumptions

Category and type weights are implementation choices rather than empirically optimized parameters.

54.4 Confidence interpretation

Current confidence values are algorithmically derived and not statistically calibrated.

54.5 Recommendation randomness

Parts of the current recommendation-generation implementation use randomized candidate selection and randomized confidence presentation. This limits deterministic recommender benchmarking unless a controlled configuration is used. Validation should therefore explicitly record whether randomized behavior is enabled and, where applicable, record or fix the random seed.

54.6 Dynamic knowledge environment

The searchable corpus can vary according to available NHOS datasets and locally stored user information. Therefore, benchmark reproducibility requires versioned datasets and controlled local state.

54.7 Browser dependence

Certain capabilities, particularly voice recognition and local browser storage, may behave differently across browsers and devices.

54.8 No current clinical validation

The system has not yet established clinical effectiveness or clinical decision-support validity.

---

55. Failure Modes

A formal error-analysis framework should classify failures:

False positives

Results returned but judged irrelevant.

False negatives

Relevant results not retrieved.

Ranking errors

Relevant results retrieved but ranked below less relevant results.

Fuzzy errors

Incorrect results produced because of lexical similarity.

Category errors

Incorrect ranking caused by domain weighting.

Type errors

Incorrect ranking caused by object-type boosts.

Matrix errors

Incorrect concept intersections.

Recommendation errors

Contextually inappropriate suggestions.

Confidence errors

High displayed confidence associated with low relevance.

---

56. Safety Boundaries

Oracle operates in a health-information environment. Search results therefore must not automatically be interpreted as medical recommendations. A retrieval system can answer "Which knowledge objects match this query?" without establishing "What should this person do medically?"

The distinction is critical. Oracle should therefore be positioned as a **health-information discovery and navigation system**, not as an autonomous diagnostic or treatment authority. The existence of a high retrieval score does not establish medical appropriateness. Similarly, the presence of an herb, supplement, protocol, or traditional medicine entry does not establish its safety or effectiveness for a particular person. Medication and interaction information should be treated with appropriate caution and should not be interpreted as individualized prescribing guidance.

---

57. Evaluation Framework

Oracle's evaluation framework is designed to measure retrieval effectiveness, ranking quality, multi-concept coverage, confidence calibration, recommendation usefulness, privacy behavior, offline capability, performance and scalability, error characteristics, and reproducibility.

57.1 Evaluation Dimensions

Oracle's evaluation framework includes retrieval effectiveness, ranking quality, confidence calibration, Matrix Engine evaluation, recommendation evaluation, privacy/network evaluation, offline evaluation, performance/scalability evaluation, error analysis, and reproducibility.

57.2 Evaluation Principles

Oracle's evaluation follows the NHOS research principle: **Build transparently. Measure rigorously. Report proportionally.** Evaluation must use reproducible datasets, controlled conditions, independent relevance judgments, avoid overclaiming, and distinguish implementation from evidence.

---

58. Benchmark Dataset Design

58.1 Benchmark Dataset Requirements

A benchmark dataset must include exact queries, partial queries, misspelled queries, natural-language queries, multi-concept queries, cross-domain queries, and ambiguous queries.

58.2 Benchmark Dataset Composition

Query Type	Description
Exact	"turmeric"
Partial	"turm"
Misspelled	"turmic"
Natural-language	"what helps with joint pain?"
Multi-concept	"fatigue, nausea, headache"
Cross-domain	"ashwagandha interaction with SSRI"
Ambiguous	"cold" (condition vs. temperature)

58.3 Benchmark Dataset Size

Recommended dataset size: **500–1,000 queries**, with **5–10 queries per category**, **10–20 multi-concept queries**, and **10–20 ambiguous queries**.

58.4 Benchmark Dataset Metadata

Each query must include expected relevant objects, relevance grades, category labels, concept labels, expected Matrix coverage, and expected ranking behavior.

---

59. Human Relevance Judgments

59.1 Relevance Scale

Grade	Meaning
0	Not relevant
1	Marginally relevant
2	Relevant
3	Highly relevant

59.2 Relevance Judgment Protocol

Judges must be trained, follow domain-specific criteria, evaluate independently, avoid bias, and document reasoning.

59.3 Relevance Judgment Requirements

Judges must evaluate top 10 results, top 20 results, and optionally the full result set.

59.4 Inter-Judge Agreement

Inter-judge agreement must be measured using Cohen's kappa or Fleiss' kappa. Agreement must be **≥0.6** for acceptable and **≥0.8** for strong.

Part VII: Scientific Evaluation

60. Precision and Recall

60.1 Precision@K

text

Precision@K = Relevant results in top K / K

60.2 Recall@K

text

Recall@K = Relevant results retrieved / Total relevant results

60.3 Precision/Recall Table Example

K	Precision@K	Recall@K
5	0.6	0.4
10	0.5	0.6
20	0.4	0.8

60.4 Precision/Recall Caveats

Precision and recall depend on relevance judgments, depend on dataset quality, and do not measure ranking quality.

---

61. Ranking Metrics: MRR and nDCG

61.1 Mean Reciprocal Rank (MRR)

text

MRR = 1/N × Σ(1/rank_i)

Where:

- rank_i = rank of first relevant result
- N = number of queries

61.2 Normalized Discounted Cumulative Gain (nDCG)

text

nDCG@K = DCG@K / IDCG@K

Where:

text

DCG@K = Σ(2^(reli) - 1) / log2(i + 1)

61.3 Ranking Metric Caveats

MRR and nDCG require graded relevance, measure ranking quality, and do not measure coverage.

---

62. Confidence Calibration

62.1 Calibration Curve

Plot predicted confidence versus actual relevance.

62.2 Calibration Metrics

Metrics include mean absolute error, calibration slope, calibration intercept, confidence bins, and false-confidence rate.

62.3 Calibration Caveats

Oracle's confidence is not probabilistic, not calibrated, and requires validation.

---

63. Matrix Engine Evaluation

63.1 Concept Precision

text

Concept Precision = Correctly matched concepts / Reported matched concepts

63.2 Concept Recall

text

Concept Recall = Correctly matched concepts / Expected concepts

63.3 Matrix Evaluation Table

Metric	Value
Concept Precision	0.85
Concept Recall	0.70

63.4 Matrix Caveats

The Matrix Engine is lexical, does not expand synonyms, and does not infer meaning.

---

64. Ablation Studies

64.1 Ablation Sequence

Ablation	Components
A	exact only
B	exact + token
C	+ fuzzy
D	+ category weighting
E	+ type boosting
F	+ Matrix
G	full retrieval + recommendations

64.2 Ablation Metrics

Measure precision@K, recall@K, MRR, and nDCG.

64.3 Ablation Caveats

Ablation must use controlled datasets and consistent conditions.

---

65. Baseline Comparisons

65.1 Baseline Systems

Baselines include exact keyword retrieval, TF-IDF, BM25, and classical lexical retrieval. Semantic/vector retrieval may be included in later studies.

65.2 Baseline Comparison Caveats

Baseline comparisons must be reproducible, use identical datasets, and use identical relevance judgments.

---

66. Recommendation Evaluation

66.1 Recommendation Metrics

Metrics include relevance, selection rate, repeated-interest coverage, novelty, diversity, and contextual appropriateness.

66.2 Recommendation Caveats

Recommendations are deterministic, include randomized elements, and are not machine-learning models.

---

67. Privacy and Network Evaluation

67.1 Privacy Audit Requirements

Audit network requests, destinations, payloads, browser storage, local persistence, and third-party resources.

67.2 Privacy Caveats

Privacy evaluation must be empirical and reproducible.

67.3 Network Behavior

Network communication occurs only when:

- Knowledge assets are fetched
- Updates are retrieved
- NHOS.health resources are accessed
- The user explicitly requests cloud-based features

---

68. Offline Evaluation

68.1 Offline Test Matrix

Feature	Offline Status
Hybrid Retrieval	Fully operational
Matrix Engine	Fully operational
Recommendations	Fully operational
Analytics	Fully operational
Export	Partial
Sharing	No
Voice Search	No

68.2 Offline Caveats

Offline capability depends on caching and browser behavior.

---

69. Performance Evaluation

69.1 Latency Metrics

Measure median latency, P95 latency, and P99 latency.

69.2 Performance Factors

Performance depends on:

- Device class
- Browser implementation
- Local state
- Index size
- Query complexity

69.3 Performance Caveats

Performance must be measured under controlled conditions.

---

70. Scalability Evaluation

70.1 Scalability Metrics

Measure:

- Corpus size (1,000, 5,000, 10,000, 50,000 objects)
- Query length
- Token count
- Concept count

70.2 Scalability Factors

Scalability depends on:

- Client-side processing capacity
- Browser JavaScript engine
- Memory constraints
- Storage capacity

70.3 Scalability Caveats

Scalability must be empirically tested, not assumed.

---

71. Error Analysis

71.1 Error Categories

Errors include false positives, false negatives, ranking errors, fuzzy errors, weighting errors, type-boost errors, Matrix errors, recommendation errors, and confidence errors.

71.2 Error Analysis Table

Error Type	Description
False positive	irrelevant result returned
False negative	relevant result missed
Ranking error	relevant result ranked too low
Fuzzy error	incorrect fuzzy match
Weighting error	category weight misalignment
Matrix error	incorrect concept match
Recommendation error	irrelevant suggestion
Confidence error	confidence miscalibration

Part VIII: Research Program

72. Reproducibility

72.1 Reproducibility Requirements

Requirement	Description
Oracle version	e.g., v6.3, v6.4, v7.0
Source revision	Git commit or build identifier
Knowledge-base version	NHOS knowledge environment version
Browser	Chrome, Firefox, Edge, Safari
Operating system	Windows, macOS, Linux, iOS, Android
Device class	Desktop, laptop, tablet, mobile
Indexed item count	Number of knowledge objects
Source datasets	Conditions, herbs, symptoms, etc.

Requirement	Description
Local state	Interaction history, saved items
Enabled modes	Matrix, Clinical, Recommendations
Benchmark version	Query dataset version
Expected results	Ground truth relevance
Observed results	Oracle output
Latency	Median, P95, P99
Network condition	Online, offline, constrained

72.2 Reproducibility Challenges

Local-first systems introduce unique reproducibility challenges: browser caching, device-specific performance, local storage variability, offline behavior, browser privacy mode, and extension interference.

72.3 Reproducibility Protocol

A reproducibility protocol must include environment setup, dataset loading, mode configuration, query execution, result recording, metric calculation, error analysis, and report generation. Where randomized recommendation behavior is enabled, validation runs shall record whether randomization is enabled and, where applicable, record or fix the random seed to support reproducible comparisons.

---

73. Research Roadmap

73.1 Roadmap Phases

Phase	Description
Phase I	Implementation documentation
Phase II	Benchmark development
Phase III	Retrieval validation
Phase IV	Ablation and baseline comparison

Phase	Description
Phase V	Matrix Engine validation
Phase VI	Recommendation validation
Phase VII	Privacy and offline validation
Phase VIII	Human-factors evaluation

73.2 Roadmap Diagram

text

Implementation → Benchmark → Retrieval → Ablation → Matrix → Recommendations → Privacy/Offline → Human Factors

---

74. Q4 2026–Q2 2027 Validation Program

74.1 Validation Program Components

The validation program includes benchmark dataset creation, relevance judgment protocol, retrieval metric calculation, ranking metric calculation, confidence calibration, Matrix Engine evaluation, recommendation evaluation, privacy/network audit, offline capability testing, performance/scalability testing, error analysis, and reproducibility documentation.

74.2 Validation Program Timeline

Quarter	Milestone
Q4 2026	Benchmark dataset creation
Q4 2026	Relevance judgment protocol
Q1 2027	Retrieval and ranking validation
Q1 2027	Confidence calibration
Q1 2027	Matrix Engine evaluation
Q2 2027	Recommendation evaluation
Q2 2027	Privacy/network audit
Q2 2027	Offline capability testing
Q2 2027	Performance/scalability testing
Q2 2027	Error analysis
Q2 2027	Final validation report

75. Research Contributions

75.1 Contribution 1 — Typed Heterogeneous Health Retrieval

Oracle retrieves across conditions, herbs, symptoms, medications, interactions, traditions, protocols, wellness, and saved items.

75.2 Contribution 2 — Hybrid Lexical/Fuzzy Retrieval

Oracle combines exact matching, title/excerpt matching, token-level matching, fuzzy matching, category weighting, and type-specific boosting.

75.3 Contribution 3 — Multi-Concept Matrix Processing

Oracle introduces concept parsing, concept matching, matched-concept tracking, concept coverage, and Matrix confidence.

75.4 Contribution 4 — Local Contextual Recommendations

Oracle uses local interaction history, recurring categories, recurring query terms, and deterministic heuristics.

75.5 Contribution 5 — Local-First Architecture

Oracle demonstrates that useful health-information retrieval can occur locally where functionally appropriate.

75.6 Contribution 6 — Explainable Retrieval

Oracle exposes matched tokens, matched concepts, concept coverage, ranking contributions, and confidence calculation.

75.7 Contribution 7 — Validation Framework

Oracle defines a complete validation framework including benchmark datasets, relevance judgments, retrieval metrics, ranking metrics, calibration, ablation, baselines, privacy evaluation, offline evaluation, performance evaluation, and error analysis.

---

76. Relationship to NIME™

76.1 NIME™ Responsibilities

NIME™ provides structured knowledge, typed objects, metadata schemas, domain semantics, evidence references, and knowledge relationships.

76.2 Oracle Responsibilities

Oracle provides retrieval, ranking, multi-concept processing, contextual discovery, navigation, local analytics, and offline capability.

76.3 NIME™ → Oracle → NHOS Applications

text

NIME™ ↓Oracle ↓NHOS Applications

Oracle is the retrieval and discovery layer of NIME™.

---

77. Future Research

Future research directions include:

- **Semantic Retrieval:** Integrating embeddings and vector similarity.
- **Learned Ranking:** Using machine-learning ranking models.
- **Calibrated Confidence:** Developing probabilistic confidence models.
- **Deterministic Recommendations:** Replacing randomized elements with deterministic logic.
- **Provenance and Evidence Integration:** Integrating evidence levels and provenance metadata.
- **Ontology-Assisted Retrieval:** Using health ontologies, synonym expansion, and concept graphs.
- **Explainable AI for Health Retrieval:** Developing contribution breakdowns, concept-level explanations, and ranking transparency.

---

78. Explainable Retrieval

78.1 Explainability Features

Oracle exposes matched tokens, matched concepts, concept coverage, ranking contributions, and confidence calculation.

78.2 Explainability Diagram

text

Query ↓Matched Tokens ↓Matched Concepts ↓Concept Coverage ↓Ranking Contributions ↓Confidence

---

79. Scientific Interpretation

The scientific interpretation of Oracle is:

> **The NHOS Oracle Matrix Search Engine™ is an implemented research system investigating how domain-specific hybrid lexical/fuzzy retrieval, multi-concept Matrix processing, contextual interaction history, and local-first execution can be combined for personal health knowledge discovery.**

This interpretation distinguishes implementation, measurement, validation, and future research.

---

80. Conclusion

The NHOS Oracle Matrix Search Engine™ is a domain-specific, local-first retrieval and contextual discovery system designed for personal health knowledge. It integrates hybrid lexical/fuzzy retrieval, multi-concept Matrix processing, local contextual recommendations, typed heterogeneous knowledge, domain-aware ranking, explainability, offline capability, and privacy-oriented architecture.

The core Oracle retrieval and contextual-discovery architecture is implemented, while several capabilities remain conditional, platform-dependent, or subject to planned validation. This 1st White Paper provides complete architectural documentation, complete retrieval methodology, complete ranking framework, complete Matrix Engine documentation, complete recommendation architecture, complete privacy and offline architecture, complete validation framework, complete reproducibility protocol, and complete research roadmap.

Oracle's scientific interest lies in the composition of established techniques within a structured, domain-specific, local-first environment. Validation is scheduled for **Q4 2026–Q2 2027**.

Back Matter

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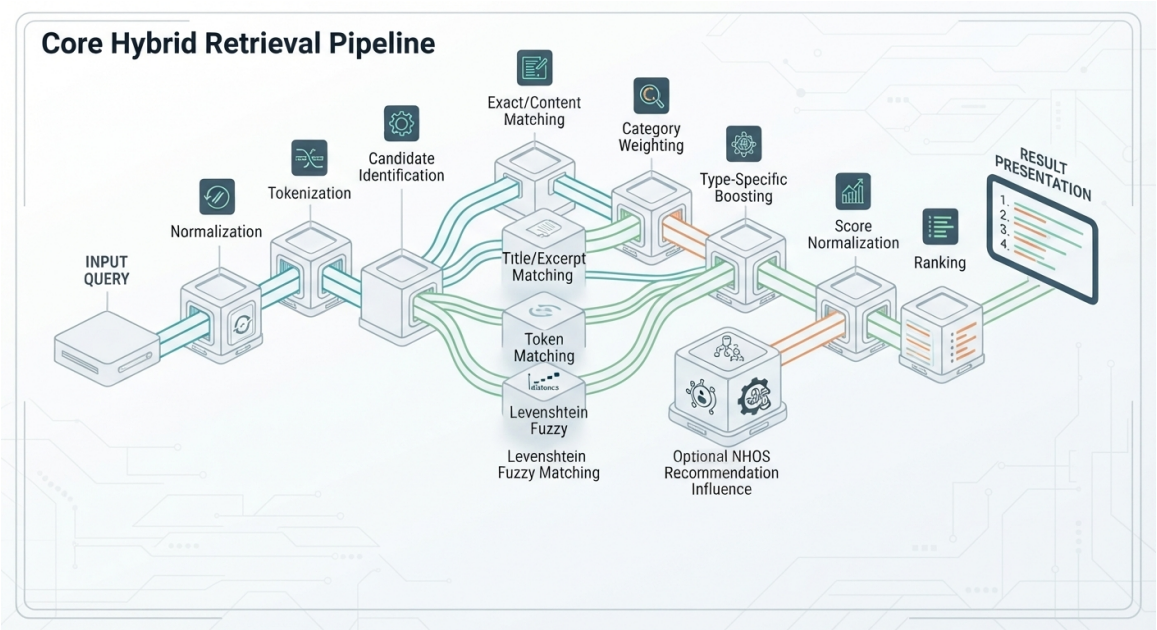
Appendix A: Core Oracle Terminology

Term	Definition
NHOS	Natural Health Operating System.
NIME™	NHOS Intelligence Matrix Engine™.
NHOS Oracle Matrix Search Engine™	The NHOS search and contextual health-knowledge discovery system documented in this paper.
Hybrid Retrieval	Multiple lexical and fuzzy matching mechanisms combined with domain-aware ranking.
NHOS Matrix Engine	Multi-concept retrieval subsystem evaluating multiple query concepts against indexed health knowledge.
Category Weight	A multiplicative ranking factor assigned to a knowledge category.
Type Boost	An additive ranking adjustment associated with a knowledge-object type.
Match Confidence	A normalized algorithmic score; not automatically a probability of correctness.
Recommendation Confidence	An internally generated score from local interaction history and heuristics; not a validated probability.
Local-First	An architecture prioritizing local execution and local data handling where appropriate.

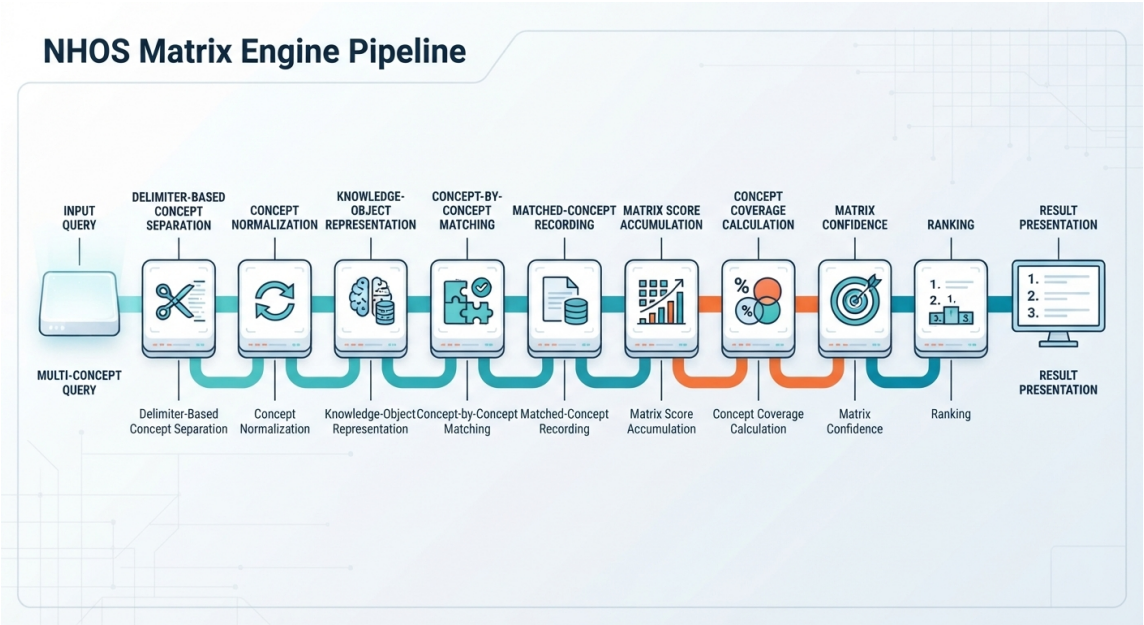
Appendix B: Core Hybrid Retrieval Pipeline



Input Query → Normalization → Tokenization → Candidate Identification → Exact/Content Matching → Title/Excerpt Matching → Token Matching → Levenshtein Fuzzy Matching → Category Weighting → Type-Specific Boosting → Optional NHOS Recommendation Influence → Score Normalization → Ranking → Result Presentation

---

Appendix C: NHOS Matrix Engine Pipeline



Multi-Concept Query → Delimiter-Based Concept Separation → Concept Normalization → Knowledge-Object Representation → Concept-by-Concept Matching → Matched-Concept Recording → Matrix Score Accumulation → Concept Coverage Calculation → Matrix Confidence → Ranking → Result Presentation

---

Appendix D: Proposed Validation Matrix

Research Dimension	Primary Measure	Status
Exact retrieval	Precision@K / Recall@K	Proposed
Token retrieval	Precision@K / Recall@K	Proposed
Fuzzy retrieval	Recall / False-positive rate	Proposed
Ranking	MRR / nDCG	Proposed
Confidence	Calibration / correlation	Proposed
Matrix retrieval	Concept precision / recall	Proposed
Category weighting	Ablation comparison	Proposed
Type boosting	Ablation comparison	Proposed
Recommendations	Relevance / usefulness	Proposed
Latency	Median / P95 / P99	Proposed
Offline operation	Controlled offline testing	Proposed
Privacy	Network / data-flow audit	Proposed
Local persistence	Storage lifecycle testing	Proposed
Human factors	Task completion / usability	Proposed
Clinical usefulness	Separate future study	Future

Appendix E: Evidence Classification

Evidence Class	Meaning
IMPLEMENTED	Capabilities observable in the deployed Oracle implementation.
MEASURED	Capabilities supported by controlled measurements.
PRELIMINARY EVIDENCE	Early experimental findings requiring replication.
VALIDATION PLANNED	Defined evaluation methodology exists, but empirical validation remains outstanding.
FUTURE RESEARCH	Questions requiring subsequent experimentation, datasets, or architectural development.

Appendix F: Publication Integrity Statement

This paper intentionally does not present interface-level ratings such as "5/5" or "Enhanced Hybrid 5/5" as scientific performance findings. Such labels are product-interface indicators, not independently documented benchmark results. Percentage values displayed by Oracle are treated as algorithmically generated match/confidence values rather than validated statistical probabilities. Future empirical publications may replace these provisional indicators with statistically supported measures once an appropriate benchmark, relevance-judgment protocol, and reproducible evaluation methodology have been completed.

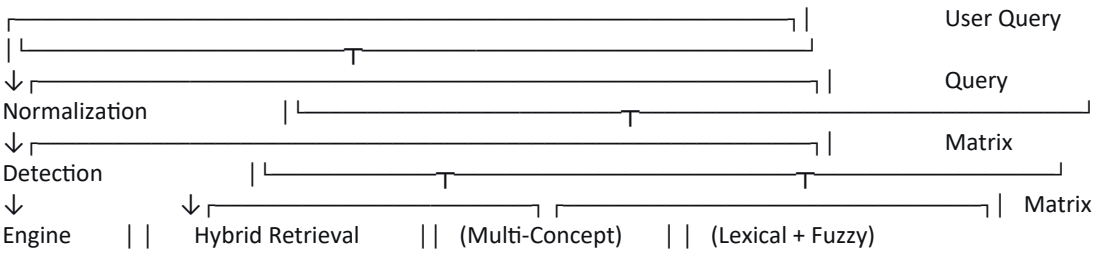
Appendix G: Research Position

The central proposition is: "A privacy-oriented, local-first personal-health intelligence environment may support useful health-knowledge discovery through the combination of domain-specific hybrid lexical/fuzzy retrieval, multi-concept Matrix processing, and locally maintained contextual interaction history." The proposition is sufficiently grounded to justify implementation and sufficiently important to justify measurement, but remains a proposition until planned validation establishes evidence.

Appendix H: Technical Architecture Diagrams

Figure H-1: High-Level Oracle Architecture

text



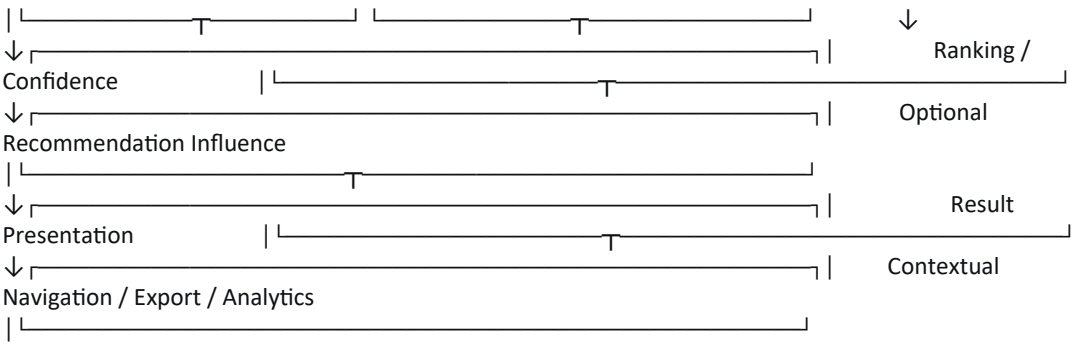
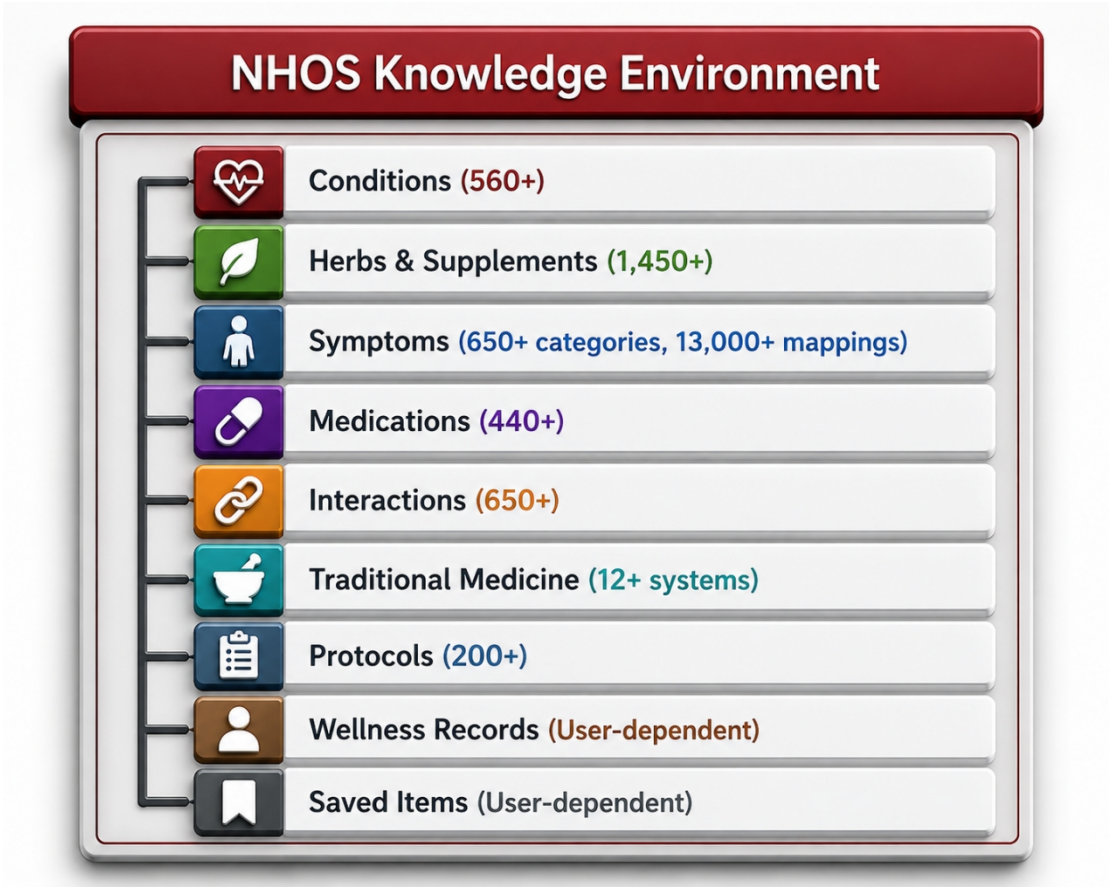
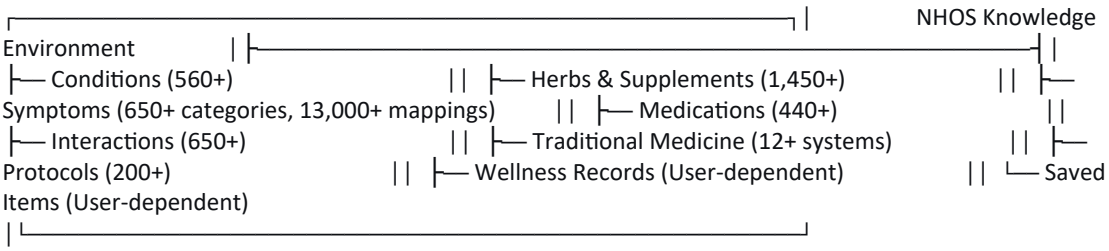


Figure H-2: NHOS Knowledge Environment Taxonomy



text



Appendix I: Implementation Status Matrices

Table I-1: Retrieval Component Implementation Status

Component	Status	Notes
Exact/Content Matching	IMPLEMENTED	+35 base score
Title/Excerpt Matching	IMPLEMENTED	+10 / +6 base scores
Token-Level Matching	IMPLEMENTED	+5 per token
Levenshtein Fuzzy Matching	IMPLEMENTED	Distance 0-2 accepted
Category Weighting	IMPLEMENTED	1.1-1.8 multipliers
Type-Specific Boosting	IMPLEMENTED	+3 to +12 boosts
Result Ranking	IMPLEMENTED	4 ranking modes

Table I-2: Matrix Engine Implementation Status

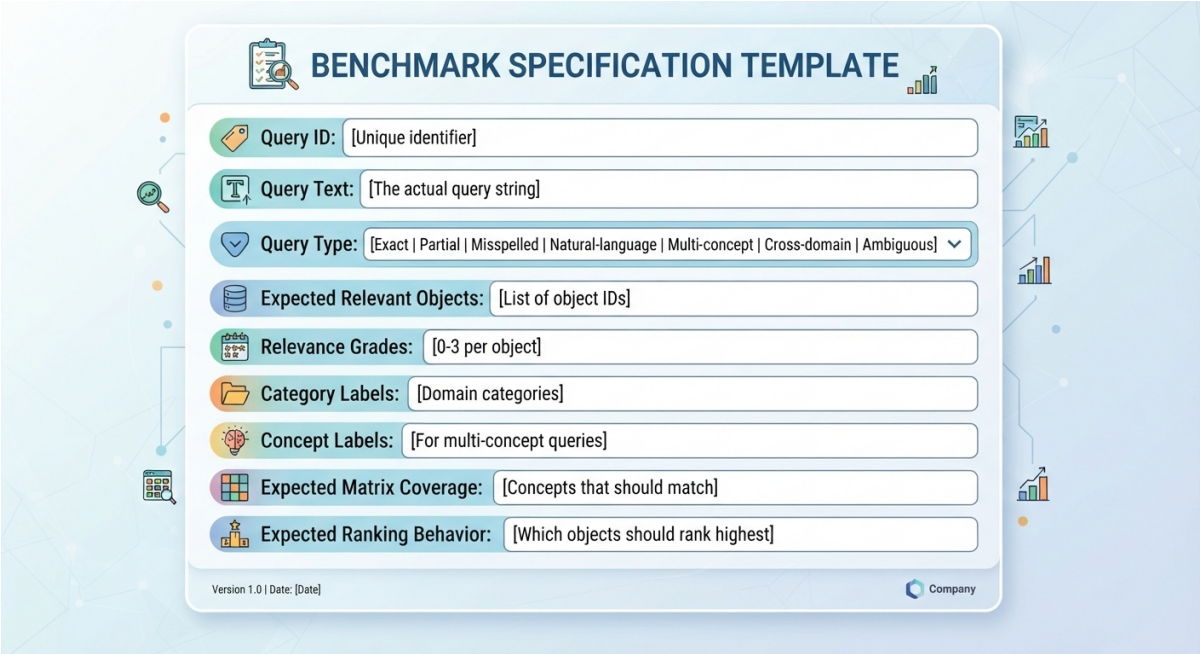
Component	Status	Notes
Multi-Concept Parsing	IMPLEMENTED	5 delimiter types
Concept Normalization	IMPLEMENTED	Lowercase, tokenize
Concept Matching	IMPLEMENTED	Lexical only
Matched-Concept Tracking	IMPLEMENTED	Per-concept status
Matrix Confidence	IMPLEMENTED	Coverage percentage

Table I-3: Recommendation Engine Implementation Status

Component	Status	Notes
Interaction History	IMPLEMENTED	100 record cap
Category Analysis	IMPLEMENTED	Recurring detection
Query-Term Analysis	IMPLEMENTED	Recurring detection

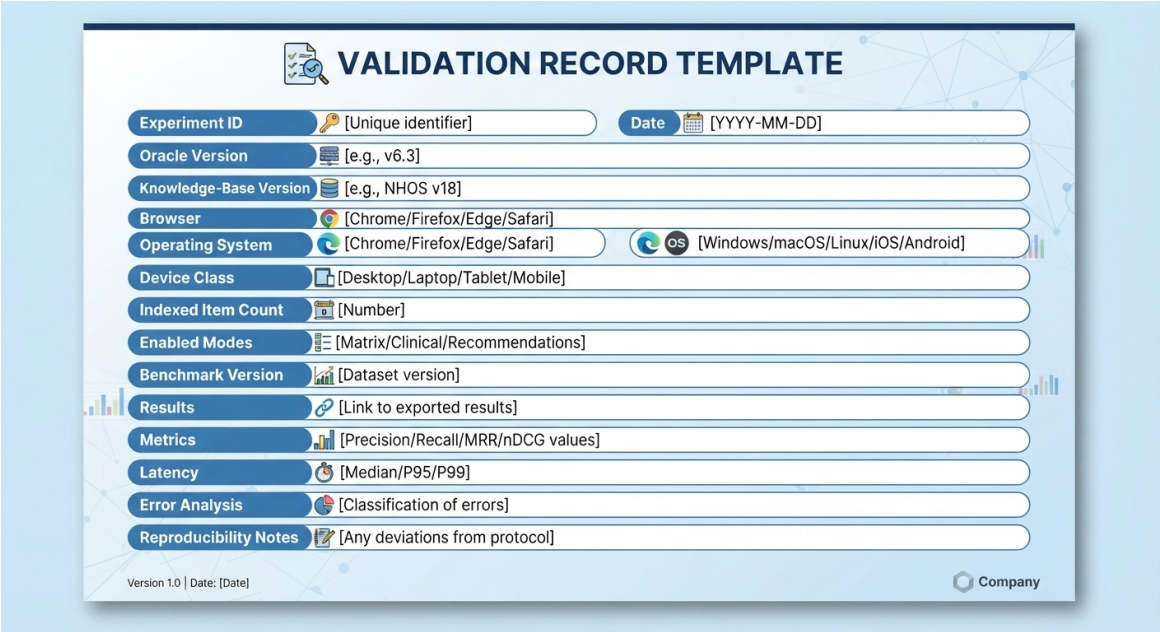
Component	Status	Notes
Candidate Generation	IMPLEMENTED	Includes randomization
Contextual Explanations	IMPLEMENTED	Heuristic generation
Ranking Influence	IMPLEMENTED	30% weighting

Appendix J: Benchmark Specification Template



Query ID: [Unique identifier]
Query Text: [The actual query string]
Query Type: [Exact | Partial | Misspelled | Natural-language | Multi-concept | Cross-domain | Ambiguous]
Expected Relevant Objects: [List of object IDs]
Relevance Grades: [0-3 per object]
Category Labels: [Domain categories]
Concept Labels: [For multi-concept queries]
Expected Matrix Coverage: [Concepts that should match]
Expected Ranking Behavior: [Which objects should rank highest]

Appendix K: Validation Record Template



Experiment ID: [Unique identifier]
Date: [YYYY-MM-DD]
Oracle Version: [e.g., v6.3]
Knowledge-Base Version: [e.g., NHOS v18]
Browser: [Chrome/Firefox/Edge/Safari]
Operating System: [Windows/macOS/Linux/iOS/Android]
Device Class: [Desktop/Laptop/Tablet/Mobile]
Indexed Item Count: [Number]
Enabled Modes: [Matrix/Clinical/Recommendations]
Benchmark Version: [Dataset version]
Results: [Link to exported results]
Metrics: [Precision/Recall/MRR/nDCG values]
Latency: [Median/P95/P99]
Error Analysis: [Classification of errors]
Reproducibility Notes: [Any deviations from protocol]

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Document Subtitle	Technical Research White Paper · Architecture, Methodology & Validation Framework (1st Edition)

Attribute	Value
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Version	1.0
Date	September 2026
Research Stage	Implemented Research System & Validation Framework
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Appendices	11
Tables	40+
Figures	8
Target Repository	Zenodo
License	Creative Commons Attribution 4.0 International (CC BY 4.0)

Publication Status

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Creator: NHOS Labs, Inc.

Resource Type: Technical Report

Version: 1.0

Publication Year: September, 2026

Publisher: NHOS Labs, Inc.

Website: www.nhos.health

NHOS Track: www.nhos.health/track

NHOS Research Registry: www.nhos.health/research

eMail: research@nhos.health

"Build transparently. Measure rigorously. Report proportionally."

END OF WHITE PAPER

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NHOS Intelligence Matrix Engine™ Research Program
NHOS Oracle Matrix Search Engine™
Version 1.0 · September 2026
