

Data-Informed Key Opinion Leader Identification and Ethical Advisory-Board Orchestration in Healthcare

An Evidence-Based Framework for Digital KOL Outreach

Dr Sadhana Gadia, Varun Gadia

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Structured Abstract

Background: Key opinion leader (KOL) engagement is widely used in medical affairs, continuing professional education, scientific exchange, advisory boards, and evidence dissemination. Digital platforms can make expert discovery and outreach more systematic, but ranking clinicians solely by publication counts, social-media visibility, prescribing proxies, or commercial attractiveness can create scientific, ethical, privacy, and compliance risks.

Objective: This article examines KOL outreach as a healthcare-platform capability, using Hidoc Dr.'s publicly described KOL Outreach service as the product context, and synthesizes evidence from implementation science, research assessment, network analysis, professional codes, transparency regulation, privacy law, and responsible artificial-intelligence guidance. It proposes a governance-oriented model for identifying, segmenting, inviting, and evaluating experts without treating algorithmic scores as substitutes for human medical judgment.

Methods: A narrative evidence synthesis was undertaken using publicly accessible product information and authoritative sources including the World Health Organization (WHO), US Centers for Medicare & Medicaid Services (CMS), National Institute of Standards and Technology (NIST), pharmaceutical-industry codes, research-assessment guidance, and peer-reviewed implementation-science literature. The analysis emphasizes principles that are transferable across specialties and jurisdictions rather than claiming measured performance for the Hidoc platform.

Results: Evidence supports a multidimensional approach to expert identification. Relevant dimensions include scientific contribution, topic fit, clinical context, peer-network position, educational activity, geographic relevance, recency of expertise, diversity, and declared conflicts. Local opinion leaders can influence professional practice, but effects are heterogeneous and context dependent. Bibliometric and network indicators can improve search efficiency, yet each has known biases. Governance therefore requires transparent selection criteria, human review, conflict-of-interest controls, fair-market-value processes, privacy safeguards, auditability, and separation of scientific objectives from promotional pressure.

Conclusion: Digital KOL outreach is most defensible when designed as a decision-support and workflow system rather than an automated influence-ranking engine. A platform such as Hidoc Dr. can create value by combining specialty and geographic discovery with structured qualification, compliant outreach, advisory-board operations, documentation, and post-engagement evaluation. Prospective validation should measure relevance, representativeness, process quality, scientific usefulness, compliance, and unintended bias—not merely engagement volume.

Keywords: Key opinion leaders; medical affairs; advisory boards; digital health; expert identification; social network analysis; bibliometrics; healthcare professional engagement; artificial intelligence; governance; compliance

1. Background

Healthcare organizations routinely need external clinical expertise. The requirement may arise when a medical-affairs team is mapping an evolving therapeutic area, when a scientific society is assembling a panel, when a sponsor is planning an advisory board, when educators

are selecting faculty, or when a digital platform is trying to connect a relevant specialist with a scientific programme. Historically, expert identification has depended heavily on internal field knowledge, publication searches, conference programmes, referral networks, and prior relationships. These methods remain valuable, but they are difficult to scale and may reproduce familiar networks.

Digital KOL outreach attempts to make this process more structured. Hidoc Dr.'s public services page describes KOL Outreach as a capability for connecting healthcare brands with medical experts by specialty and geography, with potential applications including CMEs, advisory boards, webinars, panel discussions, and clinical campaigns [1]. This description establishes a practical product context, but it does not by itself establish clinical effectiveness, ranking accuracy, or superiority. Those outcomes require prospective evaluation.

The central methodological problem is that "influence" in medicine is not a single measurable property. A highly cited investigator may be an ideal scientific adviser for a phase III evidence discussion but a poor choice for a community-practice implementation panel. A clinician with modest publication output may be the most trusted local educator in a region. A prolific social-media commentator may have reach but limited subject-matter depth. Conversely, an internationally recognized subspecialist may have extraordinary expertise but little relevance to a local formulary or care pathway. KOL identification should therefore be framed as expert-task matching under governance constraints, not as a universal leaderboard.

Implementation science provides an important foundation. Reviews of local opinion leaders have found that opinion-leader interventions can improve professional practice, although effect sizes and certainty vary across settings and implementation strategies [2]. This heterogeneity matters: identifying an expert is only the first step. The mechanism by which that expert contributes—peer education, contextual interpretation, consensus formation, barrier identification, or scientific critique—must fit the objective.

Modern data environments add new possibilities. Publication databases, clinical-trial registries, conference programmes, professional profiles, specialty information, geographic data, referral or collaboration networks, and digital engagement signals can be combined to discover experts who might otherwise be missed. Yet these same data sources introduce measurement bias, privacy questions, conflicts of interest, and the risk of mistaking visibility for expertise. The appropriate goal is therefore augmentation of medical-affairs judgment with traceable evidence.

2. Product and Service Analysis: KOL Outreach as a Platform Capability

Hidoc Dr. publicly positions its KOL Outreach service around specialty-based and location-based identification and outreach, including use in CMEs, advisory boards, webinars, panels, and clinical campaigns [1]. A defensible platform architecture can be conceptualized as five linked layers: discovery, qualification, segmentation, engagement orchestration, and evaluation.

Discovery should begin with the scientific question. Instead of asking "Who are the top cardiologists?", a user should define a narrower problem: for example, "Which interventional cardiologists in western India have recent scientific or educational activity in complex PCI and experience relevant to tertiary and high-volume referral settings?" The latter formulation produces a reproducible search target and reduces the temptation to equate prestige with relevance.

Qualification converts candidate names into structured evidence profiles. A profile might include specialty, subspecialty, practice setting, geography, institutional affiliations, recent publications, trial participation, guideline or society roles, conference faculty activity, teaching contributions, declared interests, and prior interactions. The platform should preserve source provenance and dates because expert status is dynamic. An individual's topic relevance can change as research programmes, institutional roles, and therapeutic evidence evolve.

Segmentation should be task-specific. Useful categories may include global scientific experts, national experts, regional or local practice leaders, emerging investigators, educators, digital communicators, trialists, and implementation leaders. These categories

are not hierarchical. They represent different forms of expertise. An advisory board about unmet needs in tier-2 cities, for example, may benefit more from regional practice leaders than from an exclusively metropolitan faculty.

Engagement orchestration covers invitation, scheduling, consent and contracting workflows, briefing materials, meeting logistics, disclosure capture, documentation, and follow-up. This operational layer is frequently undervalued. A scientifically sound expert list can still fail if outreach is repetitive, poorly timed, non-transparent, or inadequately documented.

Evaluation closes the loop. The platform should not define success as the number of KOLs contacted or the acceptance rate alone. More meaningful measures include whether invited experts matched the stated scientific need, whether the final panel was sufficiently diverse, whether the discussion generated actionable scientific insights, whether conflicts were disclosed and managed, whether payments and documentation were compliant, and whether the same small network was repeatedly selected without justification.

Importantly, this framework does not assume that Hidoc currently automates every element described above. It distinguishes the company's publicly stated outreach capability from a proposed evidence-based operating model. Such separation is essential in a publication: product descriptions can establish intended functionality, while performance claims require empirical data.

3. Evidence Base for Identifying Medical Experts

Three evidence traditions are particularly relevant: implementation science, bibliometrics, and social-network analysis.

Opinion-leader interventions have long been studied as a strategy for changing healthcare-professional behaviour. The Cochrane literature indicates that local opinion leaders may improve compliance with desired professional practice, but the magnitude of benefit is variable and the underlying interventions are heterogeneous [2]. This argues against a simplistic assumption that any prominent physician will reliably change practice. Context, credibility, peer similarity, implementation design, and the nature of the recommended behaviour all matter.

Bibliometrics can help characterize scientific contribution. Publications, citations, authorship position, topic-specific output, and recency can provide useful signals, particularly when identifying investigators with deep engagement in a narrow scientific domain. However, responsible research-assessment initiatives have repeatedly warned against reducing scholarly quality to journal-level metrics or single-number indicators. The San Francisco Declaration on Research Assessment (DORA) and the Leiden Manifesto emphasize qualitative judgment, field differences, transparency, and the limitations of metrics [3,4]. For KOL discovery, the implication is direct: citation counts can be one feature, but they should not become the definition of expertise.

Network analysis offers a different perspective. Scientific collaboration networks, co-authorship networks, referral networks where legally and ethically available, and professional interaction networks can reveal individuals who bridge communities or occupy central positions. Measures such as degree centrality, betweenness centrality, eigenvector centrality, and community structure can be informative. Yet network position is dependent on the network being measured. A person central in an academic co-authorship graph may not be central in community clinical practice. Data completeness can also systematically disadvantage clinicians whose work is less visible in indexed databases.

Digital signals add another layer. Online educational activity, professional social-media participation, webinar faculty history, and digital content engagement can identify "digital opinion leaders." These signals may be particularly useful for communication-oriented programmes, but they are vulnerable to popularity bias, platform demographics, coordinated amplification, and conflation of audience size with scientific reliability. A robust model should therefore distinguish scientific authority, clinical relevance, educational influence, and digital reach as separate dimensions.

A practical scoring model should be interpretable. Rather than producing a mysterious composite score, a system can display component domains and evidence. For example: topic expertise, recency, clinical-context fit, educational activity, network role,

geographic relevance, and conflict/compliance status. Weighting should change according to the use case. An oncology trial-advisory panel might emphasize trial leadership and disease-specific publications; a regional diagnostic-stewardship programme might emphasize local practice credibility and implementation experience.

Human review remains essential. Medical-affairs professionals should be able to inspect why a candidate surfaced, correct misclassification, identify missing experts, and document the rationale for final selection. This design aligns with the broader principle in responsible AI that automated systems should support accountable human decision-making rather than obscure it [5,6].

4. International Examples and Use Cases

The same KOL-discovery infrastructure can support materially different use cases.

In scientific advisory boards, the objective is usually to obtain independent expert insight on evidence gaps, clinical pathways, trial design, unmet need, or implementation barriers. The selection process should therefore maximize relevance and diversity of perspective rather than promotional reach. A panel examining an emerging therapy might include trial investigators, high-volume clinicians, community practitioners, methodology experts, and where appropriate allied professionals or patient representatives. Overconcentration of participants from one institution or prior sponsor network can narrow the discussion.

For continuing medical education or scientific webinars, faculty selection may emphasize teaching ability in addition to scientific expertise. An excellent investigator is not automatically an effective educator. Historical faculty performance can be assessed through non-promotional measures such as clarity, completion of learning objectives, quality of audience questions, and peer review of content. Commercial metrics should not be allowed to displace educational quality.

For guideline or consensus-related landscape mapping, a platform can identify authors of recent guidelines, systematic reviews, major trials, and relevant society statements. However, guideline authorship itself can be associated with declared relationships that need to be understood. The purpose of the system is not to exclude anyone with an interest but to make relationships visible and manageable.

For regional evidence dissemination, geographic relevance becomes more important. Healthcare systems differ in access, diagnostics, reimbursement, referral patterns, and workforce. A national expert may explain the evidence, while a respected local clinician can interpret feasibility. This combination is consistent with the implementation-science observation that social and contextual credibility influences uptake.

Emerging-expert programmes represent another valuable use case. If discovery relies only on citations, society leadership, or prior industry engagement, the same established individuals will dominate. Algorithms can intentionally search for early- and mid-career clinicians with recent topic-specific publications, trial involvement, high-quality educational contributions, or growing network connectivity. Such discovery should not lower scientific standards; it should broaden the search space.

Internationally, transparency rules shape how expert engagement is perceived. In the United States, CMS Open Payments maintains a public database of payments from applicable manufacturers and group purchasing organizations to covered recipients, including physicians and certain other healthcare professionals [7,8]. This makes payment transparency a practical reputational consideration as well as a reporting requirement. Global industry codes similarly emphasize legitimate need, written agreements, appropriate remuneration, and separation of professional services from inducements. A digital platform operating across markets must therefore support jurisdiction-specific workflows rather than assuming a single global compliance template.

5. Advisory-Board Design, Fair Market Value, and Conflict Governance

An advisory board is defensible when there is a genuine scientific or business need for advice, the number and expertise of participants are proportionate to that need, compensation reflects bona fide services, and the meeting is not a disguised reward for prescribing or purchasing behaviour. These principles appear across major pharmaceutical-industry codes and transparency regimes.

A KOL platform can operationalize these principles before an invitation is sent. The requestor should record the objective, the expertise required, the rationale for the proposed number of advisers, and the expected work product. Candidate selection should then be linked to those requirements. This creates an auditable chain from need to selection.

Conflict of interest should be treated as information to manage, not merely a binary exclusion flag. Relevant relationships may include consultancy, research funding, speaker activity, institutional roles, intellectual property, guideline participation, competitor relationships, and other interests. The significance of a relationship depends on the question being discussed. A trial investigator may be uniquely qualified to interpret a dataset while simultaneously requiring explicit disclosure.

Fair-market-value processes are equally important. Compensation should be based on legitimate services, expertise, time, and applicable market methodology, not on prescribing potential or commercial value. The platform can support standardized documentation, approval workflows, contracting status, and payment records. In the United States, reportable transfers may become publicly visible through Open Payments [7,8]. In other jurisdictions, local codes and laws may impose different disclosure or documentation requirements.

Meeting design should protect scientific independence. Briefing materials should clearly state the questions to be answered. Moderators should be able to challenge consensus and draw out minority views. Outputs should distinguish observations from validated evidence. If voting or structured consensus methods are used, the method should be specified in advance.

The post-meeting phase is also part of governance. Minutes should accurately capture themes without falsely attributing consensus. Action items should be linked to the original objective. Repeated engagement of the same experts should be periodically reviewed for necessity and representativeness. A mature platform should make it easier to ask, “Why was this person selected?” and “What scientific value resulted?” rather than merely documenting that a meeting occurred.

6. Privacy, Data Protection, and Responsible AI

Expert discovery can involve personal data even when the individuals are healthcare professionals and much of the information is publicly available. Names, affiliations, professional histories, online behaviour, geographic information, inferred interests, and interaction histories can collectively create detailed profiles. Organizations should therefore establish a lawful basis for processing, purpose limitation, data minimization, retention rules, access controls, and mechanisms for correction where applicable.

The risk increases when algorithms infer characteristics that are not directly supplied by the clinician. A system may infer therapeutic interests from content consumption, prescribing-related datasets, publication topics, or digital interactions. Such inferences can be useful for relevance matching but can also be wrong or overly intrusive. Data provenance and confidence should be visible to reviewers.

WHO guidance on AI for health emphasizes autonomy, human well-being and safety, transparency, accountability, inclusiveness, and sustainability [5]. Although a KOL-ranking tool is generally not a diagnostic medical device, these principles remain relevant because the system influences professional opportunities, visibility, and commercial-scientific interactions. NIST’s AI Risk Management Framework similarly provides a voluntary structure for governing, mapping, measuring, and managing AI risk [6].

Bias can enter at multiple stages. Publication databases may underrepresent local journals. English-language indexing can advantage certain regions. Citation metrics can favor older investigators and large institutions. Historical engagement data can perpetuate prior selection bias. Social-media metrics can privilege

clinicians who have more time or incentive to build public profiles. Geography filters can inadvertently exclude experts who serve cross-regional populations. Gender and career-stage inequities can be amplified if the model learns from historical invitation patterns.

Mitigation should include dataset audits, subgroup analysis, explainable feature displays, human override, periodic revalidation, and explicit diversity review. The system should allow users to search beyond the highest-ranked candidates. Randomized or stratified exploration can sometimes help discover qualified experts outside established networks, provided scientific eligibility thresholds remain intact.

Security is another governance domain. Expert profiles, contracts, payment records, meeting materials, and interaction histories may be commercially sensitive. Role-based access, encryption, logging, retention controls, and incident-response procedures should be proportionate to the data. Cross-border data transfers require particular attention when a platform serves multinational organizations.

Finally, AI-generated summaries of expert profiles or publications should be clearly treated as secondary interpretations. Source documents should remain accessible, and hallucination-sensitive fields—such as credentials, trial roles, or disclosures—should not be accepted without verification. The objective is faster synthesis, not automated fabrication of authority.

7. Regulatory and Industry-Code Considerations

Compliance architecture should be modular because KOL engagement sits at the intersection of privacy, transparency, anti-inducement rules, promotional regulation, medical-affairs standards, contracting, and corporate policy.

In the United States, Open Payments is a national transparency programme that publishes certain payments and transfers of value from reporting entities to covered recipients [7,8]. A platform supporting US engagements should therefore capture recipient identity accurately, classify transfers appropriately, and maintain records that can be reconciled with reporting systems.

Industry codes provide additional operational principles. The IFPMA Code addresses interactions with healthcare professionals and organizations, including consultancy and service arrangements [9]. EFPIA and national member-association codes similarly establish standards for professional interactions in Europe [10]. The ABPI Code provides detailed UK requirements around meetings, consultancy, disclosure, and promotional conduct [11]. These codes are not interchangeable with law, but they shape expected industry practice.

In India, the Uniform Code for Pharmaceutical Marketing Practices (UCPMP) 2024 strengthened the formal framework governing pharmaceutical marketing practices and interactions with healthcare professionals [12]. Organizations using KOL outreach in India should map workflows to the current code, internal standard operating procedures, tax requirements, and any applicable professional or institutional rules.

The platform should separate scientific and promotional workflows where organizational policy requires it. Medical-affairs engagements should have documented scientific objectives and appropriate review. Product endorsements, promotional speaker programmes, independent medical education, and advisory services are not the same activity and should not be collapsed into a generic “KOL campaign.”

Jurisdictional configuration is preferable to hard-coded global assumptions. Required disclosures, contract clauses, approval routes, hospitality limits, payment transparency, data residency, and consent language can differ. A rules engine can assist, but final compliance ownership remains with the sponsoring organization and its qualified legal/compliance personnel.

8. Proposed Evaluation Methodology

A digital KOL-outreach capability should be evaluated prospectively. The following methodology is proposed for a platform such as Hidoc Dr.; it is a research framework, not a report of completed results.

Study design: A mixed-methods prospective evaluation could compare platform-assisted expert identification with the organization's existing manual process across multiple therapeutic-area briefs. Each brief would define the scientific objective, target geography, required expertise, exclusions, and desired panel composition before candidate discovery begins.

Reference standard: An independent multidisciplinary committee—medical affairs, relevant clinicians, methodology expertise, and compliance representation—could review blinded candidate profiles. Rather than declaring a single “true KOL,” the committee would rate task-specific suitability. Inter-rater agreement should be reported.

Primary performance measures: Precision among the top candidates can estimate how many surfaced experts are judged suitable for the defined task. Recall is harder because the universe of valid experts is unknown, but a pooled candidate set from platform search, manual search, society sources, and literature search can provide a pragmatic denominator. Ranking quality can be assessed using normalized discounted cumulative gain or similar information-retrieval measures if ordinal expert relevance ratings are available.

Representativeness measures: Geographic distribution, institution concentration, career stage, gender where lawfully and appropriately collected, practice setting, and prior-engagement concentration should be examined. The objective is not demographic quota-setting by algorithm; it is detection of systematic blind spots and overreliance on established networks.

Process measures: Time from brief to qualified shortlist, number of manual corrections, proportion of profiles with verifiable source provenance, invitation response rate, contracting cycle time, disclosure completeness, and documentation errors can be measured. Time savings should be reported only if observed prospectively.

Scientific-value measures: For advisory boards, requestors and independent reviewers can rate whether the meeting answered the prespecified questions, generated novel insights, identified evidence gaps, or changed a research or implementation plan. These outcomes should use structured scales and qualitative analysis rather than promotional metrics.

Safety and governance measures: False credential attribution, outdated affiliations, missed conflicts, duplicate identities, inappropriate targeting, privacy complaints, compliance deviations, and algorithmic subgroup disparities should be tracked as adverse process events. A system that finds experts quickly but creates unverifiable profiles would not be successful.

Comparative design: Where feasible, therapeutic briefs could be randomized to manual-first versus platform-assisted-first discovery, with crossover after the initial shortlist. This would allow comparison of unique qualified experts discovered by each method while reducing therapeutic-area confounding.

Qualitative component: Interviews with medical-affairs users and invited clinicians can examine perceived relevance, transparency, burden, trust, and fairness. Experts should be asked whether outreach accurately represented why they were selected and whether the scientific purpose was clear.

Statistical analysis: Confidence intervals should accompany performance estimates. Subgroup analyses should be prespecified. If an algorithm is updated during the study, versioning must be recorded. Missing data should be reported transparently. The evaluation should avoid post hoc claims based only on favorable campaigns.

Reporting: Observational components can draw on STROBE principles, while any prediction or ranking-model study should use an appropriate model-reporting framework. Implementation outcomes can be organized using established implementation-science taxonomies [13,14]. The protocol and analytic plan should ideally be registered or time-stamped before analysis to reduce selective reporting.

This evaluation approach deliberately broadens the definition of product quality. Accuracy, diversity, explainability, operational efficiency, scientific usefulness, compliance, and user trust are all relevant. No single metric is sufficient.

9. Implementation Considerations for Healthcare Organizations

Organizations adopting a KOL-outreach platform should begin with governance rather than data volume. A steering group should define approved data sources, prohibited features, use-case categories, decision rights, escalation pathways, and minimum documentation. The same model should not automatically be used for scientific advisory boards, promotional faculty, research collaboration, and educational programmes.

Data quality management requires entity resolution. Clinicians may publish under name variants, move institutions, hold multiple affiliations, or share names with other professionals. Persistent identifiers such as ORCID can help in research contexts, while professional registration identifiers may be relevant in specific jurisdictions. Automated matching should include confidence thresholds and manual verification for consequential fields.

Taxonomy design is equally important. Specialty labels alone are often too broad. Disease, procedure, biomarker, modality, patient population, care setting, and research-method expertise can improve matching. Controlled vocabularies should coexist with free-text search because emerging scientific concepts may not yet fit established taxonomies.

Workflow integration determines adoption. Users should be able to move from brief to shortlist to internal review to invitation without repeatedly exporting spreadsheets. However, convenience should not erase checkpoints. High-risk actions—final selection, conflict approval, contracting, payment approval—should remain explicit and attributable.

Change management should address the cultural concern that algorithms will replace field medical knowledge. The better operating model treats field insight as a source of contextual evidence and algorithmic discovery as a way to widen and document the search. Disagreements between the system and experienced medical colleagues are useful signals for model improvement.

Vendor and sponsor responsibilities should be clear. The platform provider can supply tools, provenance, controls, and audit logs; the sponsoring healthcare organization remains responsible for the legitimacy of the engagement, appropriate content, contracting, payment, and jurisdiction-specific compliance. Contractual allocation of data-controller and processor roles should reflect actual processing activities.

A phased rollout is preferable. Organizations can begin with low-risk discovery and profile verification, then add workflow automation, analytics, and carefully governed AI assistance. Each phase should have acceptance criteria and monitoring. This reduces the likelihood that an opaque ranking model becomes embedded in decision-making before its biases are understood.

10. Limitations

Several limitations apply to this analysis. First, it is a narrative synthesis rather than a systematic review, and it does not estimate pooled effect sizes. Second, public information about Hidoc Dr. establishes the existence and intended applications of KOL Outreach but does not provide enough independently validated data to assess algorithmic accuracy, operational efficiency, clinical impact, or comparative performance. No such outcomes are claimed here.

Third, the concept of a KOL is itself contested. It can imply scientific leadership, peer influence, commercial categorization, or digital visibility depending on context. This article therefore prefers task-specific expert suitability wherever possible. Fourth, regulations and industry codes evolve; organizations must confirm current jurisdiction-specific requirements before implementation. Fifth, some potentially informative datasets—such as prescribing, referral, or interaction data—may be unavailable, incomplete, restricted, or inappropriate for a given purpose.

Finally, algorithmic fairness cannot be solved solely by removing protected characteristics. Historical and structural inequities can be encoded through institutions, geography, publication opportunity, network access, and prior engagement. Ongoing governance and empirical auditing are therefore required.

11. Conclusion

KOL outreach can be transformed from a relationship-dependent search process into a more systematic, evidence-traceable workflow, but only if digitalization is accompanied by governance. Hidoc Dr.'s public service description demonstrates a practical platform use case: identifying and reaching experts by specialty and geography for scientific and educational activities [1]. The larger opportunity is to make expert-task matching more transparent, reproducible, diverse, and operationally manageable.

The strongest model does not ask an algorithm to decide who is "important." It asks the system to assemble relevant evidence, widen discovery, explain why candidates match a defined brief, surface conflicts and uncertainty, support compliant engagement, and learn from structured evaluation. Human medical, scientific, and compliance judgment remains decisive.

Future research should test these systems prospectively against manual workflows and report not only engagement rates but also relevance, representativeness, scientific usefulness, data quality, compliance performance, bias, and user trust. If those standards are met, digital KOL outreach can function as responsible infrastructure for scientific exchange rather than merely another targeting mechanism.

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Author Note

This manuscript is an independent evidence-based analysis of a publicly described Hidoc Dr. service capability. It does not report a clinical trial or claim validated performance for the Hidoc platform. Product-specific performance should be established through prospective evaluation.