

Review Article

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Beyond Human Audiences in Healthcare: A Conceptual Framework for Machine-Facing Branding and Algorithmic Legibility in AI-mediated Patient Choice

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Abstract

Patients increasingly use digital systems to locate hospitals, compare health services, assess telemedicine providers, and interpret information about health care. As generative and agentic artificial intelligence becomes part of this process, a computational intermediary may retrieve, summarise, rank, or recommend healthcare organisations before a patient encounters them directly. A provider may therefore be clinically credible and meaningful to patients yet remain absent from an AI-generated consideration set, or be represented inaccurately, because its identity, services, evidence, accreditation, limitations, or access conditions are difficult for the system to interpret. This conceptual paper reframes Machine-Facing Branding for healthcare and develops the Healthcare Algorithmic Legibility Framework (HALF). The framework was constructed through a purposive, theory-building synthesis of signalling theory, source credibility, organisational legitimacy, brand equity, trust in automation, patient decision-making, health recommender systems, and guidance on ethical artificial intelligence for health. It proposes eight antecedents of healthcare algorithmic legibility: semantic clarity of services, structured provider knowledge, entity identity and disambiguation, cross-source consistency, clinical and institutional authority, verifiable trust signals, transparency and disclosure, and technical and retrieval accessibility.

These conditions are linked to agent interpretation quality, recommendation confidence, AI-mediated provider consideration, calibrated patient trust, informed preference, and provider equity. Representational fidelity is introduced as a patient-safety safeguard requiring machine-generated descriptions to remain accurate, evidence-grounded, current, and appropriately limited. Twenty propositions, nine moderating conditions, indicative measures, and a five-stage validation programme are presented. The framework focuses on how patients find and choose healthcare providers, rather than on diagnosing medical conditions or recommending treatments. It positions healthcare communication as a dual-audience responsibility: organisations must remain understandable and trustworthy to people while ensuring that authorised digital systems can interpret their services safely and accurately. The model is offered for empirical scrutiny, not as a validated clinical tool.

Keywords: Artificial Intelligence, Healthcare Communication, Patient Choice, Health Recommender Systems, Provider Selection, Trust Calibration, Patient Safety, Algorithmic Legibility

1. Introduction

Deciding where to seek healthcare has always involved uncertainty. Patients and families must often interpret service descriptions, professional credentials, accreditation, location, cost, waiting time, insurance coverage, language support, and evidence of quality. The difficulty is not simply a shortage of information. Relevant facts

are frequently dispersed across hospital websites, public registries, insurer directories, booking platforms, professional profiles, reviews, and government sources. As a result, patients may struggle to identify which provider offers the required service and whether the available information can be trusted. Artificial intelligence is beginning to alter this pathway. Generative systems can assemble

information from several sources, while recommender systems can personalise and prioritise options. More agentic systems may translate a user goal into tasks, compare alternatives, ask follow-up questions, and prepare a shortlist. In healthcare, these functions could help a patient identify a suitable hospital, diagnostic centre, pharmacy, telemedicine service, rehabilitation provider, or specialist clinic.

They could also create new risks. A fluent answer can omit a suitable provider, confuse organisations with similar names, repeat outdated information, exaggerate a service, overlook a restriction, or present a commercially influenced recommendation as neutral. The concern is therefore broader than online visibility. A healthcare organisation may be easy to find yet difficult for an intelligent system to interpret correctly. Conversely, a provider may have strong clinical capability but weak digital representation, causing evidence about its services to remain fragmented or ambiguous. This paper calls the desired property healthcare algorithmic legibility: the degree to which an AI system can identify a healthcare organisation, understand the services it is authorised and equipped to provide, connect relevant evidence to the correct entity, recognise material limitations, and represent the provider appropriately for a defined patient need.

This is not an argument for replacing professional judgement or encouraging patients to treat an AI-generated list as medical advice. The framework focuses on the early stages of a patient's healthcare journey, particularly how people identify, explore, and consider suitable providers and services. Diagnosis, triage, prescribing, and treatment choice remain outside its scope. The distinction matters because an inaccurate provider description may still affect access, delay, cost, privacy, equity, and trust, even when the system offers no clinical recommendation.

1.1. Research Objective and Questions

The paper aims to explain how healthcare organisations can be represented in ways that support accurate and responsible interpretation by intelligent agents without reducing care to promotion. Four questions guide the analysis:

- RQ1. What constitutes Machine-Facing Branding in healthcare?
- RQ2. Which information and governance conditions shape healthcare algorithmic legibility?
- RQ3. Through which mechanisms might legibility influence AI-mediated provider consideration and patient responses?
- RQ4. Which clinical, patient, technological, market, and regulatory conditions strengthen, weaken, or reverse these relationships?

1.2. Contribution

The paper makes five contributions. First, it extends healthcare

communication from a patient-facing activity to a dual-audience responsibility that also considers machine interpretation. Second, it distinguishes visibility from legibility. Third, it introduces representational fidelity as a safety-oriented standard for AI-generated provider descriptions. Fourth, it connects communication and branding theory with patient navigation, health recommender systems, and trustworthy AI. Fifth, it converts the argument into testable propositions and a staged validation programme.

1.3. Scope and Boundary Conditions

The framework applies when an AI system retrieves, compares, ranks, summarises, or recommends healthcare organisations or non-emergency services in response to a patient goal. It is most relevant to planned and preference-sensitive navigation, such as choosing a hospital for an elective consultation, identifying a diagnostic facility, comparing telemedicine providers, locating rehabilitation support, or checking whether a provider offers a particular service. It does not apply to emergency triage, autonomous diagnosis, medication selection, or treatment decisions. It also does not assume that patient choice is always available; referral rules, insurance networks, geography, clinical urgency, and public-sector allocation may sharply constrain options.

2. From Digital Healthcare Visibility to Algorithmic Legibility

Healthcare organisations have long communicated with patients through names, reputations, service lines, physician profiles, accreditation statements, public education, and patient experience. Digital channels have expanded access to these signals, but the intended interpreter remained mainly human. Search engines and directories helped users locate information, after which patients, family members, or carers compared the available options themselves. Generative and agentic systems redistribute part of this interpretive work. Before a patient sees an answer, the system may have resolved provider names, linked services to locations, compared credentials, reconciled conflicting descriptions, and selected which evidence to mention. The visible answer may therefore reflect several hidden inclusion and exclusion decisions. In healthcare, an organization should never seek greater visibility at the expense of accuracy, patient trust, or safety. The aim should be appropriate inclusion based on accurate, current, and traceable evidence.

Health recommender systems are increasingly discussed as tools that may complement decision processes and support personalised health information or interventions. Reviews also call for evaluation beyond algorithmic performance and for clearer attention to patient-care outcomes. These concerns support a shift from asking whether a provider appears in an answer to asking whether the system understands the provider correctly, explains the basis of inclusion, and preserves meaningful patient oversight. As shown in Figure 1, an intelligent agent may influence provider consideration by interpreting both the patient's request and the information available about potential providers.

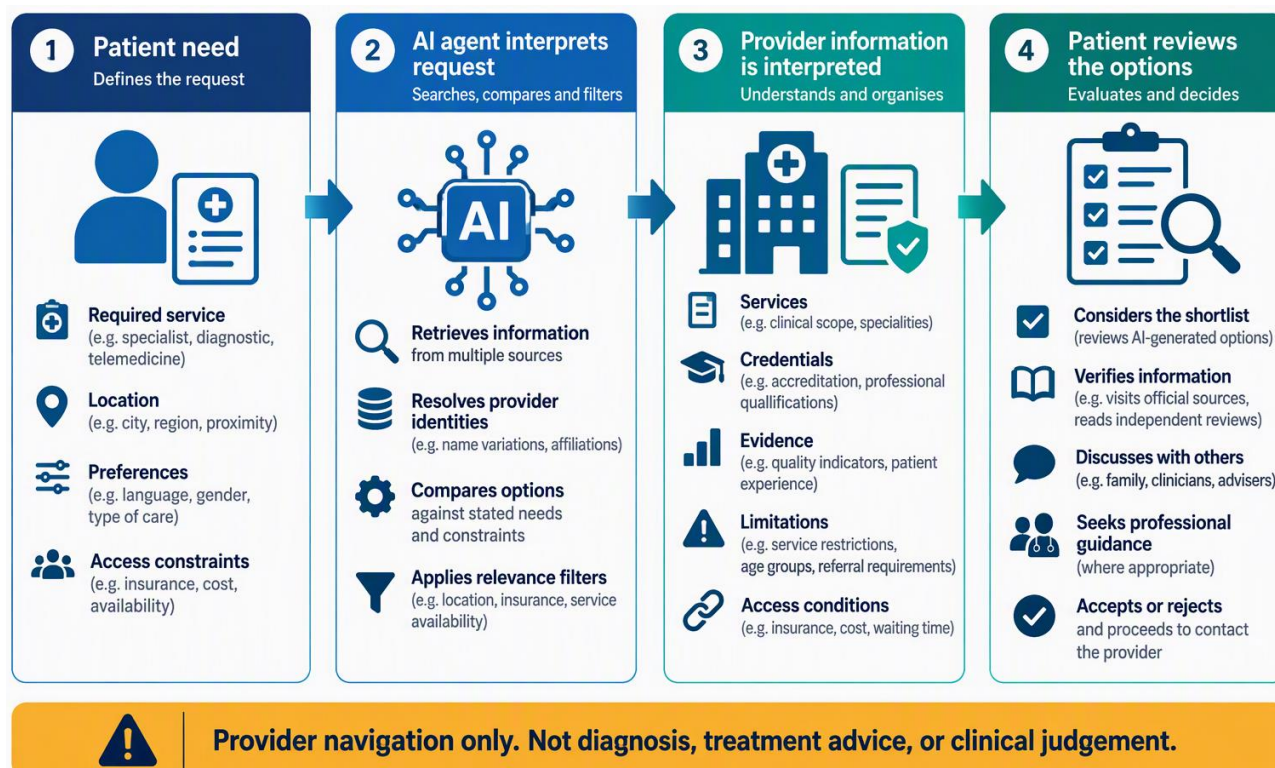


Figure 1: AI-Mediated Pathway from a Patient's Healthcare Need to Provider Consideration

3. Theoretical Foundations

3.1. Signalling Theory

Healthcare quality cannot always be fully assessed before a service is used because many aspects of care are intangible and become evident only through experience. Patients therefore rely on signals such as accreditation, professional registration, service certification, transparent outcomes, institutional affiliation, and consistent patient information. Signalling theory helps explain why verifiable and costly-to-fake indicators may reduce uncertainty. In an AI-mediated environment, a signal must also be retrievable, attributable to the correct provider, and supported by a credible source.

3.2. Source Credibility and Evidence Authority

An intelligent system may combine provider-controlled pages with regulatory records, professional registers, published evidence, insurer directories, news coverage, and patient-generated material. Source credibility draws attention to expertise and trustworthiness, while healthcare adds the need to distinguish clinical evidence from promotional assertion. Repetition across weak sources should not be treated as equivalent to independent corroboration.

3.3. Organisational Legitimacy

Healthcare providers operate within formal and social systems of legitimacy. Licensure, accreditation, recognised professional qualifications, compliance, institutional history, and alignment with accepted standards may affect whether a provider is treated

as credible. Legitimacy theory also highlights a danger: digital prominence can simulate authority without establishing it. Legibility must therefore rest on genuine standing rather than manufactured appearance.

3.4. Trust in Automation and calibrated Reliance

Trust in automation is useful only when reliance corresponds to actual capability. Patients may over-rely on a confident answer or reject a useful system because they cannot judge its limits. In healthcare navigation, calibrated trust requires understandable sourcing, visible uncertainty, opportunities to verify claims, and clear separation between provider information and clinical advice.

3.5. Patient Decision-Making, Health Literacy, and Autonomy

Patients differ in health literacy, digital literacy, language, prior experience, resources, and ability to challenge an automated recommendation. Choice is also shaped by urgency, illness burden, cost, referral arrangements, and family involvement. A responsible framework must therefore treat patient response as conditional rather than automatic and preserve the ability to compare, question, and seek human guidance.

3.6. Brand Equity and Healthcare Reputation

Brand equity theory helps explain how awareness, associations, perceived quality, and trust create value. In healthcare, however, reputation should not be separated from clinical capability, ethical conduct, and patient experience. Machine-facing communication

can support accurate consideration, but it cannot compensate for poor care. The framework therefore treats algorithmic legibility as an enabling condition rather than a direct measure of service quality.

4. Method of Conceptual Development

The paper uses a purposive, theory-building conceptual synthesis. This approach is appropriate because the immediate task is to clarify an emerging phenomenon, connect previously separate literatures, define constructs, and formulate relationships that can later be tested. It is not presented as a systematic review, meta-analysis, or empirical study. The conceptual development followed four stages. First, the phenomenon was bounded to AI-mediated discovery and preliminary consideration of healthcare organisations and non-emergency services. Second, theoretical perspectives were selected for the distinct explanatory work they perform: signalling and source credibility address evidence; legitimacy addresses

institutional standing; brand equity addresses organisational meaning and preference; trust in automation addresses reliance; and patient decision-making addresses autonomy and context.

Third, these perspectives were read alongside emerging work on generative retrieval, health recommender systems, patient safety, and governance of AI for health. Fourth, the integrated argument was translated into constructs, propositions, moderators, indicative measures, rival explanations, and a validation programme. The method has clear limits. Source selection reflects author judgement, the literature is developing rapidly, and a conceptual synthesis cannot establish prevalence, effect size, causality, or clinical benefit. Each relationship is therefore stated as a proposition rather than a finding.

5. Core Concepts and Definitions

Construct	Definition	Indicative assessment
Healthcare Machine-Facing Branding	Strategic design, verification, structuring, distribution, and governance of provider information so that AI systems can recognise and represent a healthcare organisation accurately and appropriately.	Capability scale plus external information audit.
Healthcare algorithmic legibility	Degree to which an AI system can identify a provider, distinguish it from other entities, interpret authorised services and access conditions, connect credible evidence, recognise limitations, and represent it appropriately.	Entity resolution, factual accuracy, completeness, consistency and contextual fit.
Agent interpretation quality	Accuracy, completeness, currency, consistency, relevance, and evidential grounding of an AI-generated provider representation.	Expert-coded comparison with a verified provider fact base.
Recommendation confidence	Stability and certainty with which an agent includes or prioritises a provider for a defined navigation task.	Inclusion frequency and rank stability across repeated task scenarios; system confidence only where validly available.
AI-mediated provider consideration	Inclusion of a provider in the patient’s effective set because of AI retrieval, comparison, or recommendation.	Shortlist capture after controlled agent interaction.
Representational fidelity	Extent to which an AI-generated description accurately reflects a provider’s verifiable identity, services, credentials, access conditions, current limitations, and relevant patient experience.	Independent clinical, regulatory, and communication review against verified evidence.
Calibrated patient trust	Degree to which reliance on the agent and provider representation matches their demonstrated reliability and the consequences of error.	Trust, verification behaviour, appropriate acceptance and override.
AI-mediated provider equity	Strategic and relational value arising from repeated accurate, credible, and contextually appropriate representation in AI-mediated discovery.	Longitudinal representation quality combined with patient awareness, trust, preference, and access outcomes.

5.1. Visibility, Legibility, Suitability, and Fidelity

The framework separates four important questions. First, does the healthcare provider appear in the AI-generated result? This is visibility. Second, does the AI system correctly understand the provider and its services? This is legibility. Third, is the provider appropriate for the patient’s specific needs and circumstances? This is suitability. Finally, is the information presented by the AI accurate, current, and supported by reliable evidence? This is fidelity. These four ideas are connected, but they are not the same.

A provider may appear in a result and still be described incorrectly. The AI may understand the provider accurately, but that provider may not be suitable for a particular patient. A provider may also be presented positively even though the available evidence does not fully support that description.

Figure 2 Clarifies Why Visibility, Legibility, Suitability, And Fidelity Should Be Assessed Separately Rather Than Treated As Interchangeable Concepts.

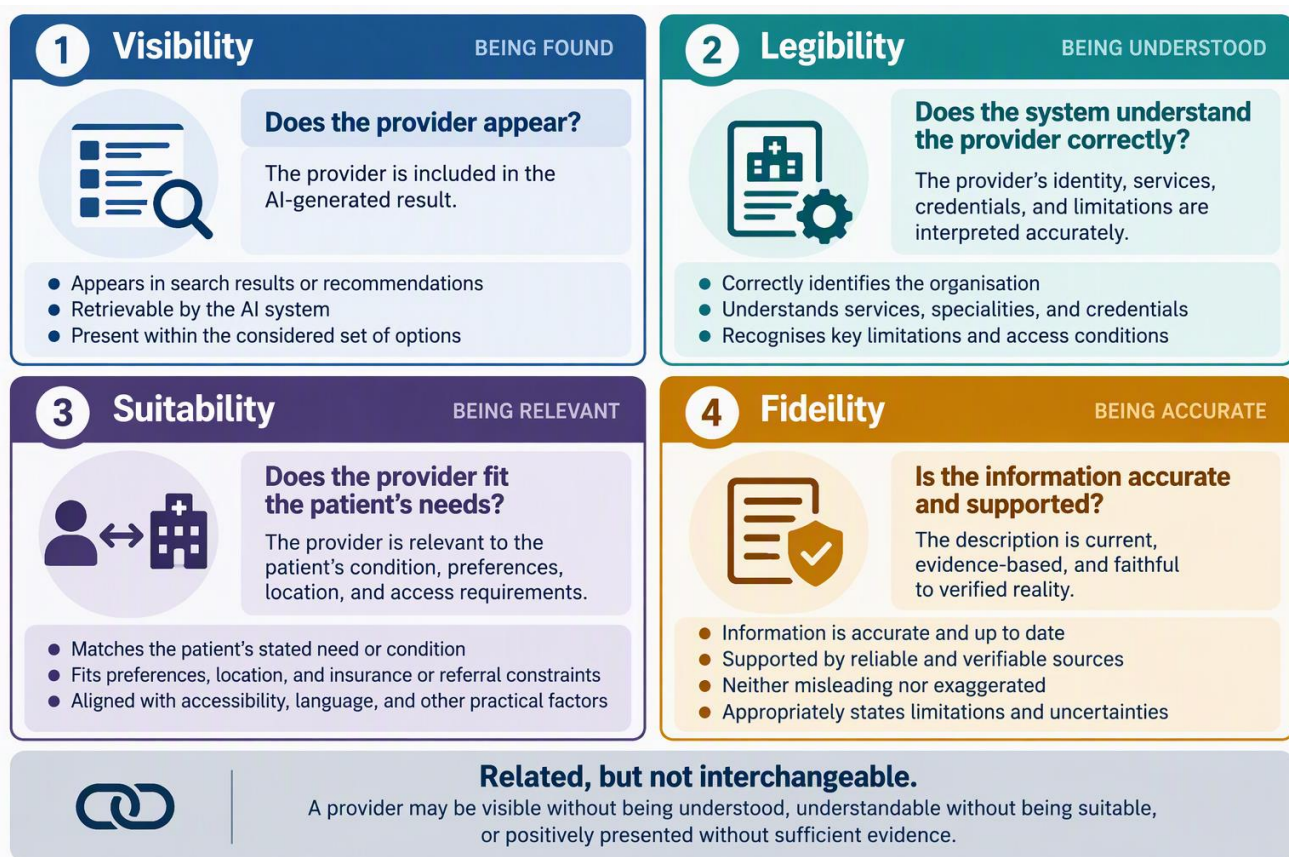


Figure 2: Four Distinct Questions for Evaluating ai-Mediated healthcare-Provider Information.

6. The Healthcare Algorithmic Legibility Framework

The Healthcare Algorithmic Legibility Framework proposes eight antecedents, two agent-level mechanisms, and a sequence of patient and organisational outcomes. The framework is intentionally conditional. It does not assume that improved legibility always produces recommendation or that recommendation always produces trust or preference.

6.1. Eight Antecedents

- **Semantic Clarity of Services.** Clear terminology for service lines, clinical scope, target populations, locations, pathways, referral requirements, and exclusions. Vague descriptions and unexplained acronyms increase ambiguity.
- **Structured Provider Knowledge.** Coherent organisation of provider, facility, professional, service, location, appointment, insurance, accessibility, and contact information in stable and machine-readable forms.
- **Entity Identity and Disambiguation.** Reliable distinction among similarly named hospitals, clinics, branches, subsidiaries, medical groups, and practitioners, including consistent identifiers and relationships.
- **Cross-Source Consistency.** Alignment of material facts across official pages, professional registers, public directories, insurer networks, maps, booking systems, and credible independent sources.
- **Clinical and Institutional Authority.** Credible evidence

of lawful operation, professional expertise, institutional affiliation, recognised accreditation, and relevant clinical capability.

- **Verifiable Trust Signals.** Traceable credentials, accreditations, certifications, quality evidence, privacy and safety policies, and claims that can be checked independently.
- **Transparency and Disclosure.** Accessible information about ownership, commercial relationships, service limitations, eligibility, prices where applicable, data practices, AI use, complaints, and the basis of claims.
- **Technical and Retrieval Accessibility.** Legitimate information that can be indexed, parsed, retrieved, updated, and attributed, with stable pages, accessible text, clear dates, and suitable metadata.

6.2. Mechanisms and Outcomes

The eight antecedents are expected to improve healthcare algorithmic legibility. Legibility should support agent interpretation quality by reducing ambiguity and strengthening evidence attribution. Where the interpreted provider fits the stated need, recommendation confidence may increase. This may influence whether the provider enters the patient's effective consideration set. Patient response then depends on trust calibration, health and AI literacy, urgency, risk, affordability, insurance rules, referral pathways, explanation quality, and the opportunity to verify the answer. Preference and provider equity should emerge only when

the digital representation is consistent with actual care and patient experience.

Figure 3 presents the proposed pathway through which provider information and governance conditions may shape AI interpretation, recommendation confidence, patient consideration, and longer-term provider equity.

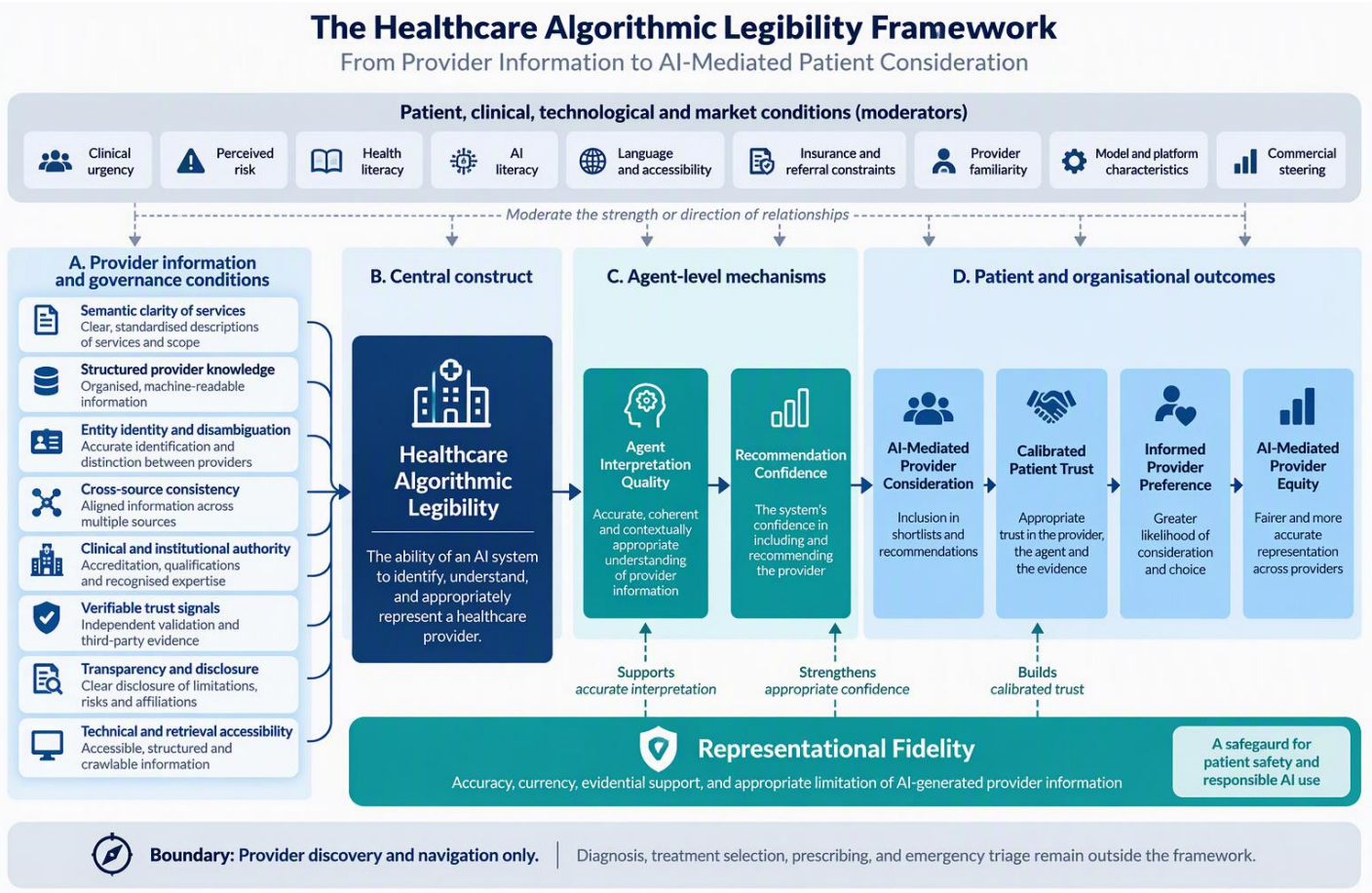


Figure 3: The Healthcare Algorithmic Legibility Framework for AI-Mediated provider Discovery and Consideration

7. Trust, Safety, and Patient Agency

Trust in AI-mediated provider choice has several objects. A patient may trust the healthcare organisation but not the agent, trust the agent but question one recommendation, or accept the information

while doubting the evidence behind it. Treating trust as a single attitude hides these differences. As illustrated in Figure 4, trust in AI-mediated provider choice involves the provider, the agent, the specific recommendation, and the supporting evidence.

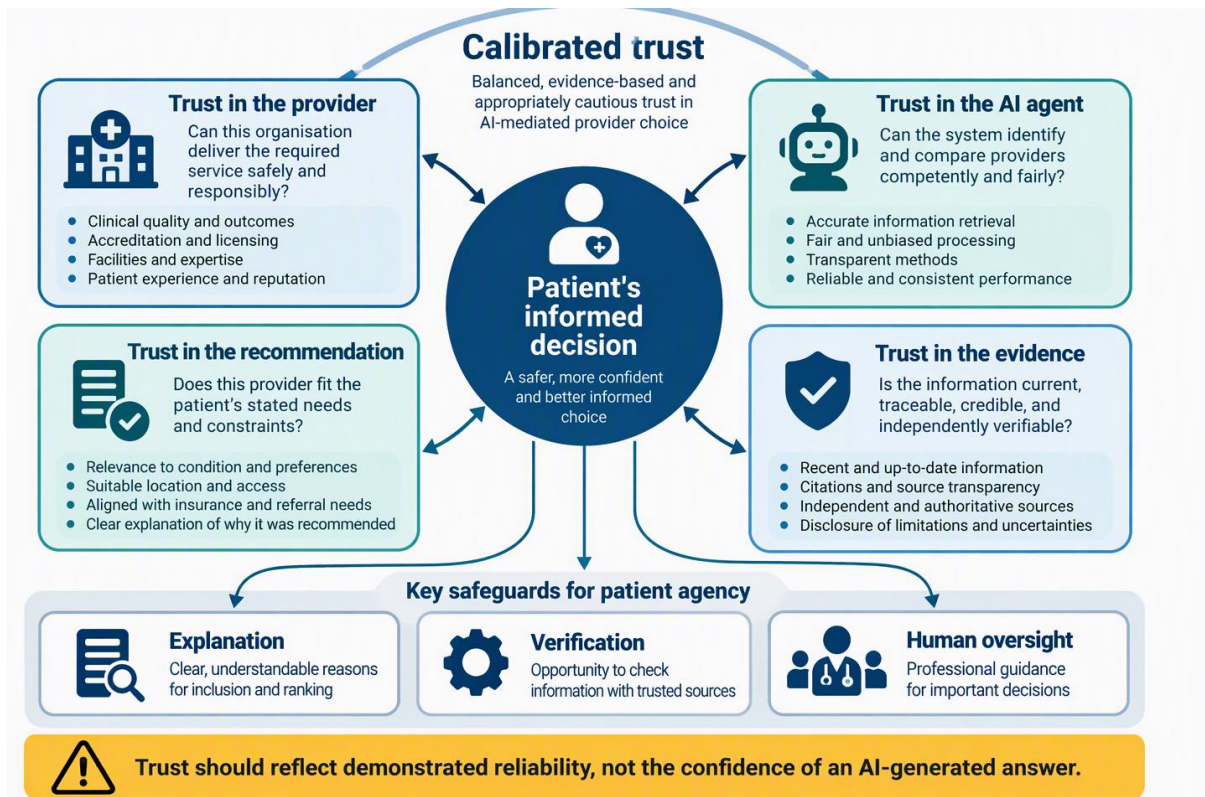


Figure 4: Objects of trust and Safeguards in ai-Mediated Healthcare-Provider Choice.

Trust object	Patient question	Required support
Provider	Can this organisation deliver the service safely and responsibly?	Credentials, capability, experience, governance and verifiable performance.
Agent	Can this system retrieve and compare providers competently and fairly?	Known scope, transparent limitations, monitoring, and accountable design.
Specific recommendation	Does this option fit my stated need and constraints?	Task-relevant explanation, alternatives, uncertainty and current information.
Supporting evidence	Can the sources behind the answer be checked?	Traceable, credible, current and independent evidence where appropriate.

Representational fidelity is the central safety safeguard. An organisation should not pursue optimisation that makes it more visible while concealing exclusions, exaggerating competence, or detaching claims from evidence. In healthcare, omission can be as consequential as falsehood. A generated answer should not imply that a facility offers emergency care, paediatric services, a particular procedure, insurance acceptance, or round-the-clock availability unless those claims are current and supported. Patient agency requires contestability. Users should be able to ask why a provider was included, what alternatives were excluded, which constraints were applied, and what sources support the description. They should also be able to recognise when the question requires professional guidance rather than automated navigation. The framework therefore favours supported choice, not passive

compliance.

8. Research Propositions

The framework advances twenty propositions. They are presented for empirical testing, refinement, and, where evidence does not support them, rejection.

- **P1.** Semantic clarity of healthcare services is positively associated with healthcare algorithmic legibility.
- **P2.** Structured provider knowledge is positively associated with healthcare algorithmic legibility.
- **P3.** Clear provider identity and effective entity disambiguation are positively associated with healthcare algorithmic legibility.
- **P4.** Cross-source consistency of material provider information is positively associated with healthcare algorithmic legibility.

- **P5.** Clinical and institutional authority is positively associated with agent interpretation quality when authority is supported by relevant and verifiable evidence.
- **P6.** Verifiable trust signals are positively associated with AI recommendation confidence for task-relevant provider selection.
- **P7.** Transparency about services, limitations, access conditions, commercial relationships, and data practices is positively associated with representational fidelity.
- **P8.** Technical and retrieval accessibility is positively associated with healthcare algorithmic legibility, provided that accessible information is current and attributable.
- **P9.** Healthcare algorithmic legibility is positively associated with agent interpretation quality.
- **P10.** Agent interpretation quality is positively associated with AI recommendation confidence when the provider satisfies the stated patient constraints.
- **P11.** AI recommendation confidence is positively associated with AI-mediated provider consideration.
- **P12.** AI-mediated provider consideration is positively associated with provider preference when patients perceive the recommendation as relevant, credible, and understandable.
- **P13.** Calibrated patient trust mediates the relationship between recommendation confidence and provider preference.
- **P14.** Representational fidelity strengthens the relationship between AI-mediated provider consideration and calibrated patient trust.
- **P15.** Health literacy and AI literacy moderate the relationship between recommendation confidence and patient reliance, with lower literacy increasing the risk of both over-reliance and disengagement.
- **P16.** Higher perceived clinical risk and urgency weaken reliance on unsupported AI recommendations and increase the value of professional human guidance.
- **P17.** Alignment between the AI-generated representation and actual care experience strengthens the relationship between provider consideration and provider equity.
- **P18.** Undisclosed commercial steering or platform self-preferencing weakens the perceived legitimacy of AI-mediated provider recommendations.
- **P19.** Repeated accurate and contextually appropriate representation is positively associated with AI-mediated provider equity over time.
- **P20.** Healthcare Machine-Facing Branding contributes to sustainable organisational advantage only when combined with authentic clinical capability, equitable access, patient-centred communication, and responsible governance.

Group	Propositions	Primary relationship	Principal basis
Antecedents	P1-P8	Information conditions -> legibility, interpretation and fidelity	Signalling; source credibility; legitimacy
Mechanisms	P9-P11	Legibility -> interpretation -> recommendation -> consideration	Information processing; recommender systems
Patient outcomes	P12-P17	Consideration, trust, reliance, preference and experience	Trust in automation; patient decision-making
Governance and equity	P18-P20	Commercial influence, longitudinal equity and responsible advantage	Legitimacy; ethics; brand equity

9. Moderating Conditions and Rival Explanations

Nine conditions may alter the proposed relationships: clinical urgency; perceived risk; patient health literacy; patient AI literacy; language and accessibility needs; insurance and referral constraints; prior provider familiarity; model, version, and retrieval architecture; and commercial steering. Their inclusion prevents the framework from treating AI-mediated choice as a uniform process. Three rival explanations require direct testing. First, incumbency may account for apparent legibility because large providers generate more content and independent coverage.

Studies should therefore control for provider size, market share, specialty breadth, and communication expenditure where data permit. Second, platform economics may determine inclusion more strongly than evidence quality. Sponsored placement, insurer relationships, or platform ownership could overwhelm the proposed information effects. Third, technical transience may limit the framework if future systems no longer depend on current forms of structured representation. Longitudinal and multi-system

designs are needed to test whether the proposed information properties remain useful across architectures.

10. Implications for Healthcare Organisations

10.1. Managerial Implications

- Conduct a healthcare algorithmic legibility audit using defined patient-navigation scenarios. Check identity resolution, service accuracy, accreditation, access requirements, location, hours, insurance information, omissions, and source attribution.
- Maintain a governed provider knowledge base containing approved facts, responsible owners, review dates, and links to authoritative evidence.
- Align public claims with clinical scope and actual patient experience. Promotional language should not exceed verified capability.
- Design for multilingual and accessible interpretation so that machine readability does not exclude patients with different languages, literacy levels, or accessibility needs.
- Monitor generated descriptions across multiple systems and

versions, but do not treat a single answer as a stable reputation score.

- Establish a correction and escalation route for inaccurate representations, with clinical, legal, communication, digital, privacy, and patient-experience oversight.
- Separate provider navigation from medical advice. Communications should state when professional assessment, urgent care, or emergency services are required.

10.2. Organisational Governance

Healthcare Machine-Facing Branding cannot sit within marketing alone. Clinical leadership must verify scope and terminology; quality teams must validate standards and outcomes; legal and regulatory teams must review claims; privacy and cybersecurity teams must govern data practices; digital teams must maintain accessible information; patient-experience teams must identify gaps between promise and lived care; and communication teams must preserve clarity and consistency. Accountability should remain human and named, even when monitoring is automated.

10.3. Ethical Implications

The framework should not be used to manipulate rankings, flood

the information environment, imitate independent authority, suppress unfavourable evidence, or steer vulnerable patients toward unsuitable services. Six principles should govern implementation: truthfulness, traceability, transparency, contestability, fairness, and human agency. These principles are consistent with the broader view that AI for health should place ethics, human rights, accountability, and public benefit at the centre of design and use.

A distributional risk also requires attention. Large and digitally mature organisations are better able to maintain structured data, multilingual content, external corroboration, and specialist governance. If legibility becomes a condition of inclusion, smaller providers and services operating in underrepresented languages may be overlooked despite offering appropriate care. Shared standards, public provider registries, low-cost verification, and platform duties to evaluate smaller organisations fairly may help reduce this asymmetry.

11. Five-Stage Validation Programme

The framework requires a staged programme of validation rather than reliance on a single study. Figure 5 presents a research pathway that moves from construct clarification to real-world evaluation.

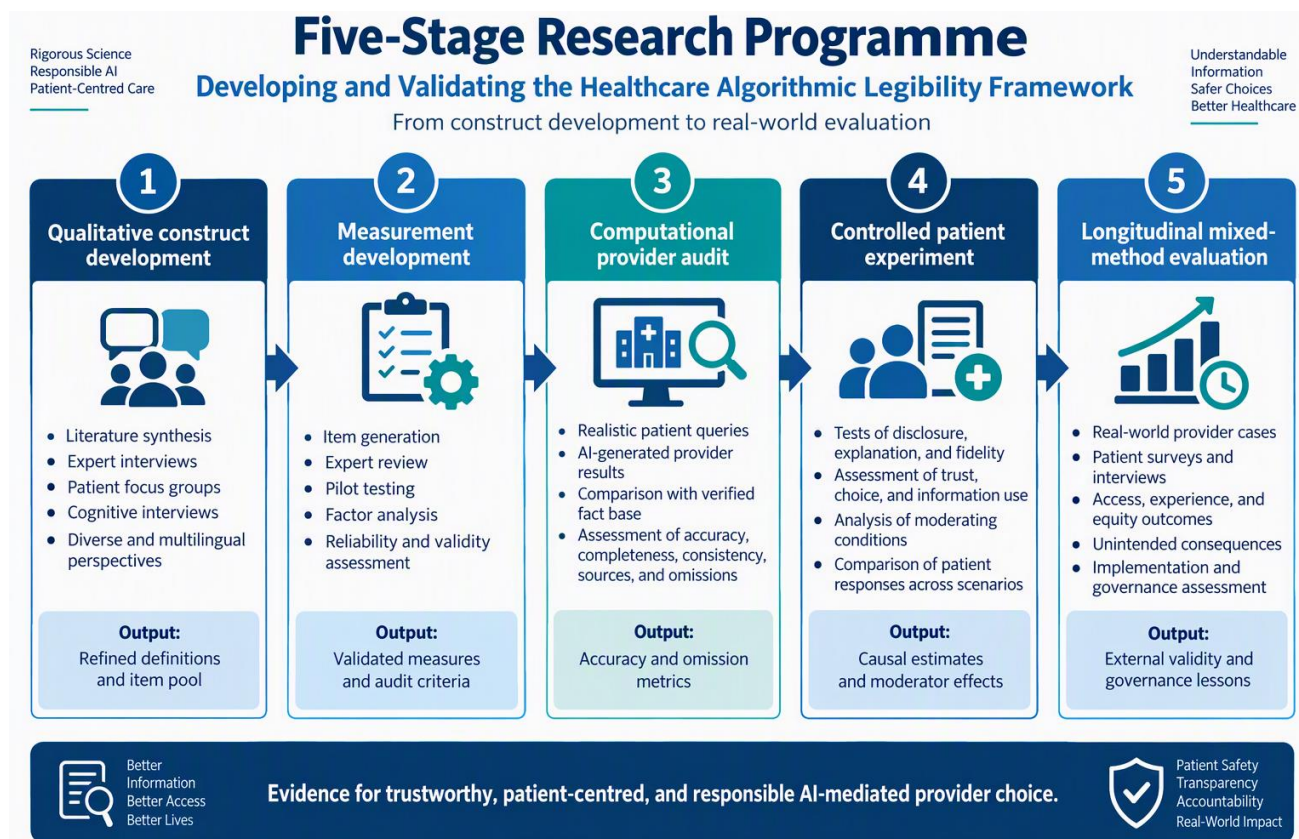


Figure 5: Five-stage programme for developing and validating the Healthcare Algorithmic Legibility Framework.

Stage	Purpose	Indicative design	Primary output
1. Qualitative construct development	Establish how patients, clinicians, navigators, regulators, and digital teams understand legibility, fidelity, trust, and agency.	Interviews, focus groups, cognitive interviewing, multilingual sampling.	Refined definitions and item pool.
2. Measurement development	Examine dimensionality, reliability, convergent and discriminant validity.	Expert review, pilot survey, exploratory and confirmatory factor analysis.	Validated scales and audit criteria.
3. Computational provider audit	Assess whether systems identify and represent providers accurately across tasks and platforms.	Repeated standardised prompts; verified fact base; blinded expert coding.	Accuracy, completeness, consistency, source and omission metrics.
4. Controlled patient experiment	Test effects of legibility, disclosure, explanation, fidelity, and sponsorship on trust and choice.	Randomised scenarios with behavioural and self-report outcomes.	Causal estimates and moderator tests.
5. Longitudinal mixed-method evaluation	Examine real-world navigation, correction, equity, and experience over time.	Multi-provider cases, logs where lawful, surveys, interviews, service-access outcomes.	External validity, unintended effects and governance lessons.

11.1. Methodological Cautions

Model and version heterogeneity must be documented because systems vary in training data, retrieval methods, source access, commercial incentives, and update cycles. Prompt wording and location can also influence outputs. Researchers should therefore preregister scenarios where possible, repeat queries, preserve output records, and avoid generalising from one system. Endogeneity is another concern. Better-resourced providers may have stronger digital information and better clinical performance. Observational studies should control for size, specialty, market position, geography, and available quality indicators. Experiments should manipulate information properties while holding provider

quality constant.

Outcome selection should extend beyond mention and rank. Appropriate measures include factual accuracy, omission of critical access conditions, source quality, consistency, patient comprehension, calibrated reliance, diversity of options, professional verification, equity of inclusion, and downstream access. Clinical outcomes should not be claimed unless a study is designed to measure them.

12. Theoretical Contributions

Contribution	Existing emphasis	Added value of HALF
Audience extension	Healthcare communication addresses patients and stakeholders.	Adds the intelligent agent as a consequential interpreter while keeping patient welfare central.
New construct	Digital visibility measures whether information appears.	Defines healthcare algorithmic legibility as accurate, evidence-grounded and context-sensitive interpretability.
Mechanism specification	Recommender research often focuses on prediction or personalisation.	Links provider information to interpretation quality, recommendation confidence and patient consideration.
Safety safeguard	Brand authenticity concerns perceived genuineness.	Introduces representational fidelity to address inaccurate or incomplete machine-generated provider accounts.
Conditional model	Technology adoption models often seek average effects.	Specifies nine moderators and three rival explanations that may weaken or reverse predicted effects.
Governance bridge	Branding and clinical governance are often treated separately.	Positions provider representation as a shared clinical, ethical, informational and communication responsibility.

13. Limitations

- The framework is conceptual. None of the propositions has been tested, and no effect size or causal relationship is established.
- The proposed constructs may overlap with information quality, digital maturity, online reputation, health literacy, provider transparency, and organisational legitimacy. Discriminant validity must be demonstrated.
- The eight antecedents may not be exhaustive or independent.
- Empirical work may combine, divide, or replace them.
- The framework simplifies differences among generative search, conversational assistants, insurer tools, provider directories, recommendation systems, and autonomous agents.
- Patient choice is constrained in many health systems. Referral pathways, insurance, geography, urgency, affordability, and capacity may matter more than recommendation.
- Provider communication cannot establish clinical quality by

itself. Legibility may improve interpretation while leaving actual care unchanged.

- The framework does not address diagnosis, treatment selection, medication advice, or emergency triage and should not be used to justify automated clinical decision-making.
- Ethical risks including commercial steering, content manipulation, fabricated authority, discriminatory exclusion, privacy loss, and automation bias remain unresolved.

14. Conclusion

Artificial intelligence is changing how patients encounter healthcare organisations. In some journeys, a person may see only the shortlist or summary produced after a system has already retrieved information, resolved identities, compared services, and selected evidence. This creates a practical and theoretical problem: a provider can be visible without being understood, understood without being suitable, or recommended without being represented faithfully. This paper reframed Machine-Facing Branding for healthcare and proposed the Healthcare Algorithmic Legibility Framework. The framework connects eight information and governance conditions with agent interpretation quality, recommendation confidence, provider consideration, calibrated trust, informed preference, and provider equity. It also introduces representational fidelity as a safeguard against optimisation that increases exposure while weakening accuracy.

The argument is not that healthcare organisations should communicate for machines instead of people. Nor is it that patients should delegate clinical judgement to an agent. The central claim is narrower: when digital systems mediate provider discovery and navigation, organisations have a responsibility to make their identity, services, evidence, limitations, and access conditions clear to both human and machine interpreters. That responsibility must remain grounded in authentic clinical capability, patient safety, fairness, and accountable human oversight. The framework is offered for examination, revision, and possible rejection through empirical research.

References

1. Aaker, D. A. (1991). Managing brand equity: Capitalizing on the value of a brand name. *New York*, 28(1), 35-37.
2. Aggarwal, P., Murahari, V., Rajpurohit, T., Kalyan, A., Narasimhan, K., & Deshpande, A. (2024, August). GEO: Generative engine optimization. In Proceedings of the 30th ACM SIGKDD conference on knowledge discovery and data mining (pp. 5-16)..
3. Ananthakrishnan, A., Milne-Ives, M., Shankar, R., & Meinert, E. (2024). Evaluation of health recommender systems: a scoping review protocol. *BMJ open*, 14(10), e083359.
4. Barbaric, A., Christofferson, K., Benseler, S. M., Lalloo, C., Mariakakis, A., Pham, Q., ... & Cafazzo, J. A. (2025). Health recommender systems to facilitate collaborative decision-making in chronic disease management: a scoping review. *Digital health*, 11, 20552076241309386.
5. Bettman, J. R. (1979). An information processing theory of consumer choice. (No Title).
6. Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of marketing research*, 56(5), 809-825.
7. Choudhury, A., & Asan, O. (2020). Role of artificial intelligence in patient safety outcomes: systematic literature review. *JMIR medical informatics*, 8(7), e18599.
8. Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, 37(1), 39-67.
9. Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the academy of marketing science*, 48(1), 24-42.
10. Lognoul, M. (2025). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act–AI Act). *Revue du Droit des Technologies de l'information*, (3-4), 145-189.
11. Goktas, P., & Grzybowski, A. (2025). Shaping the future of healthcare: ethical clinical challenges and pathways to trustworthy AI. *Journal of clinical medicine*, 14(5), 1605.
12. Hovland, C. I., & Weiss, W. (1951). The influence of source credibility on communication effectiveness. *Public opinion quarterly*, 15(4), 635-650.
13. Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the academy of marketing science*, 49(1), 30-50.
14. Jaakkola, E. (2020). Designing conceptual articles: four approaches. *AMS review*, 10(1), 18-26.
15. Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., ... & Fung, P. (2023). Survey of hallucination in natural language generation. *ACM computing surveys*, 55(12), 1-38.
16. Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *Journal of marketing*, 57(1), 1-22.
17. Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human factors*, 46(1), 50-80.
18. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational behavior and human decision processes*, 151, 90-103.
19. Morhart, F., Malär, L., Guèvremont, A., Girardin, F., & Grohmann, B. (2015). Brand authenticity: An integrative framework and measurement scale. *Journal of consumer psychology*, 25(2), 200-218.
20. OCDE. (2019). Recommendation of the council on artificial intelligence. OECD/LEGAL/0449.
21. Ohanian, R. (1990). Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. *Journal of advertising*, 19(3), 39-52.
22. Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of marketing*, 85(1), 131-151.
23. Spence, M. (1973). Job Market Signalling": The Quarterly *Journal of Economics*". LXXXVII, 3, 355-74.

-
24. Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of management review*, 20(3), 571-610.
 25. Torraco, R. J. (2016). Writing integrative literature reviews: Using the past and present to explore the future. *Human resource development review*, 15(4), 404-428.
 26. Guidance, W. H. O. (2021). Ethics and governance of artificial intelligence for health. *World Health Organization*, 1.
 27. Wang, Y., Song, Y., Wang, Y., YU, L., & Wang, J. (2024). Ethics and governance of artificial intelligence for health: guidance on large multi-modal models. *Chinese Medical Ethics*, 1001-1022.

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