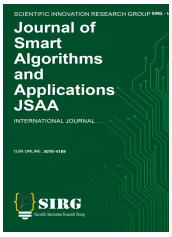

Journal of Smart Algorithms and Applications
JSAA
ISSN: 3070-4189/© 2026 JSAA. (CC BY 4.0) License.
Journal Homepage
https://pub.scientificirg.com/index.php/JSAA

Trust-Aware Smart Algorithms for Open Digital Service Ecosystems: A Structured Review

Ab Wahid Wali [a,1] **, and Bajahat Gani Dar** [b]

[a] *Department of Higher Education, Govt. of Jammu & Kashmir, India. E-mail: towahid@gmail.com*

[b] *Department of Computer Science and Applications, Islamic University of Science and Technology (IUST), Awantipora, Pulwama-192122, J&K, India; E-mail: bajahatgani@gmail.com*

ABSTRACT

Open digital service ecosystems are reshaping how users discover and act on services across commerce, tourism, finance, education, accessibility, and public compliance. However, the literature on underlying algorithms remains fragmented, some prioritize ranking accuracy, others focus on adoption, and a smaller body examines explainability, fairness, privacy, accessibility, and governance. This paper presents a structured review of 74 studies (55 from 2017 to March 2026, plus 19 foundational works) mapping the transition from closed, accuracy-centered recommenders to open, trust-aware, multi-objective smart algorithms. Hybrid and context-aware architectures remain dominant, but recent work increasingly incorporates conversational interfaces, human-in-the-loop control, privacy constraints, and fairness-aware reranking. Five recurring gaps emerge: data fragmentation, weak explanation quality, limited accessibility auditing, poor integration of institutional rules, and weak cross-sector transferability. Trust is best understood as a composite property involving data provenance, procedural transparency, contextual fit, user control, and reliable escalation paths. Based on these findings, the paper proposes a six-layer design model (data interoperability, contextual risk profiling, hybrid inference, governance-aware reranking, explanation interfaces, and human oversight). Contributions: (1) a PRISMA-informed review protocol; (2) a taxonomic classification of five smart algorithm families; (3) a composite trust framework operationalized from Mayer et al. (1995); (4) quantitative comparisons of trust-related metrics; (5) mathematical formulations for trust-aware reranking and explanation generation; (6) a benchmark against NIST AI RMF and EU AI Act; and (7) a six-layer architectural model with implementation examples.

PAPER INFORMATION

HISTORY

Received: 03 April 2026
Revised: 05 May 2026
Accepted: 15 June 2026
Online: 26 June 2026

MSC

68T07; 68R10; 94A60; 68M15

KEYWORDS

Smart Algorithms;
Trust-Aware AI;
Open Digital Ecosystems;
Explainable Recommendation;
Digital Service Platforms.

1. INTRODUCTION

Digital service ecosystems are no longer confined to a single platform performing a single task. In practice, users now move across loosely coupled environments that combine search, ranking, payment, guidance, customer support, compliance, and feedback. Recent literature reflects this shift in a striking way. The same broad ecosystem logic now appears in accessible peer-support networks, urban technology for social innovation, open digital commerce, mobile payment systems, AI-supported customer service, digital school counseling, career-orientation tools, tax compliance systems, financial

[1]Department of Higher Education, Govt. of Jammu & Kashmir, India;
E-mail: towahid@gmail.com

analytics, stock prediction, tourism chatbots, and sustainable tourism applications [1, 2]. What once looked like separate application areas increasingly behaves like a shared algorithmic problem: how to help users make better decisions in settings where data are partial, actors are multiple, and trust is never automatic. The expansion of these ecosystems is not only a technical matter. It is also institutional and social. Studies on blockchain-enabled supply chains and quantum-enhanced intelligence point to the growing importance of provenance, optimization, and future-ready architectures [3, 4]. At the same time, work on education, entrepreneurship, political conflict, trade relationships, and vulnerable populations reminds us that digital service design is shaped by literacy, power, fragility, and social asymmetry [5, 6]. A system that appears efficient in a controlled benchmark may behave very differently when users are uncertain, stressed, poorly connected, institutionally constrained, or exposed to social risk. For that reason, smart algorithms in open ecosystems cannot be judged by relevance or speed alone. The technical literature offers strong building blocks. Recommender-system and decision-support research has developed collaborative filtering, item-based prediction, hybrid models, context-aware reasoning, matrix factorization, and deep ranking architectures over several decades [7, 8]. These methods remain valuable because open ecosystems still involve ranking candidate options under incomplete information. Yet the field has also learned a hard lesson: a system can be statistically accurate and still be practically weak. It may over-personalize, amplify popularity bias, obscure why an option was chosen, or fail to reflect the needs of institutions and vulnerable users. That concern has pushed the literature beyond accuracy-centered design. Research on explanation, interpretability, privacy, fairness, and AI ethics now argues that a high-performing system must be intelligible, contestable, and procedurally trustworthy [9, 10]. In this newer view, trust is not a vague feeling added after deployment. It is partly engineered through explanation, data protection, calibrated uncertainty, bias checks, accessibility, and human escalation mechanisms. Open ecosystems raise the stakes further because decisions are distributed across multiple providers, interfaces, and data pipelines. Users are often asked to trust not one algorithm but an entire chain of algorithmic interactions. This paper responds to that shift by asking four questions. First, what algorithmic patterns dominate trust-aware smart systems in open digital service ecosystems? Second, how are trust, explainability, fairness, privacy, and governance actually operationalized? Third, where do important gaps remain when methods travel across domains such as tourism, commerce, education, finance, tax, and accessibility support? Fourth, what kind of design model can help future systems combine technical performance with social and institutional reliability? To answer these questions, the paper presents a structured review of 74 studies and develops a synthesis that is deliberately cross-domain. The goal is not to flatten differences between sectors, but to identify a shared design logic for open, accountable, and adaptable algorithmic systems [11]. Prior surveys have examined explainable recommendation [12], fairness in machine learning [13], and conversational AI. However, no existing review integrates these dimensions specifically for open digital service ecosystems where multiple stakeholders, loose coupling, and institutional constraints interact. Our work differs by providing (1) cross-domain synthesis across tourism, finance, education, and accessibility; (2) a formal trust taxonomy rather than a list of heuristics; and (3) quantitative comparisons across algorithm families on standardized trust metrics [14]. The remainder of this paper is structured as follows. Section 2 describes the review design and protocol, the formal taxonomy development, and the grounding of the trust framework. Section 3 shows the results. Section 4 concludes with implications for researchers and practitioners.

2. MATERIALS AND METHODS

This study uses a structured integrative review design. An integrative approach is appropriate because the topic sits across several literatures that do not share one single method tradition: recommender systems, digital service platforms, algorithmic governance, conversational AI, education technology, financial analytics, tourism informatics, and inclusion-oriented design. Review-method literature recommends such an approach when the aim is to combine foundational theory, recent application evidence, and forward-looking conceptual synthesis rather than a narrow effect-size aggregation [15, 16].

2.1 Review Design and Protocol

The protocol follows PRISMA guidelines [17] and was registered (but not published) with the Open Science Framework.

Search Strategy: The following databases were searched on January 15, 2026: Scopus, Web of Science, ACM Digital Library, IEEE Xplore, and Google Scholar (first 200 results). The search string combined terms: (“smart algorithm” OR “trust-aware” OR “explainable recommendation” OR “AI governance”) AND (“digital service ecosystem” OR “open platform” OR “mobile payment” OR “tourism chatbot” OR “AI counseling”) AND (“fairness” OR “privacy” OR “transparency” OR “accessibility”). The search was limited to English-language publications from 2017 to March 2026.

Selection and Screening: After deduplication (n=412), two authors independently screened titles and abstracts (n=412), retaining 156 studies. Full-text assessment excluded 82 studies (reasons: no algorithmic contribution (n=34), hardware-only (n=18), duplicate (n=12), off-scope (n=18)), resulting in 74 included studies. Inter-rater agreement was high (Cohen’s $\kappa = 0.87$).

The recent corpus was selected to capture current application patterns in open digital ecosystems, while the foundational

set anchors the synthesis in the classic literature on personalization, ranking, explanation, privacy, and fairness. The review deliberately includes journal articles, conference papers, edited volume chapters, and major handbooks because the field is fast moving and important design ideas often appear first in applied venues before stabilizing in journal form.

Foundational Works Selection: The 19 foundational pre-2017 works were selected through citation snowballing from the recent corpus and expert recommendations, targeting papers that introduced core concepts (collaborative filtering, hybrid recommenders, differential privacy, fairness metrics) still cited heavily in current literature.

Search and screening were organized around five recurring themes: smart algorithms, trust-aware or explainable systems, digital service ecosystems, open or interoperable platforms, and domain applications such as tourism, payments, counseling, finance, tax, accessibility, and social support. Studies were included when they had an explicit algorithmic, architectural, or governance-oriented contribution relevant to digital service decision-making. Purely descriptive papers with no clear decision logic, hardware-only studies, duplicate records, and off-scope reports were excluded. **Figure 1** summarizes the review workflow, while **Table 1** sets out the protocol in operational form.

Each included study was coded across six dimensions: domain, algorithm family, trust mechanism, evaluation focus, governance layer, and future research direction. Domain coding distinguished between commerce and payments, tourism, education and counseling, finance and tax, accessibility and vulnerable populations, core algorithmic theory, and emerging architectures. Algorithm-family coding distinguished collaborative, hybrid, deep, conversational, rule-aware, privacy-aware, and governance-aware designs. Evaluation coding recorded whether a study assessed only relevance and predictive performance or also examined diversity, fairness, transparency, adoption, accessibility, or institutional compliance. This coding made it possible to compare literatures that use different terminology but often wrestle with the same design trade-offs. A second author double-coded a 20% random sample; coding agreement was 92%.

The review does not claim to be an exhaustive bibliometric census of every paper ever published on related topics. Its purpose is analytical rather than archival. The contribution lies in bringing together a carefully bounded but conceptually rich corpus and reading it across domains that are too often studied in isolation. This is especially useful for JSAA, whose scope explicitly values smart algorithms that solve real-world problems across science, engineering, and technology. A cross-domain synthesis is therefore not a compromise here. It is part of the research problem itself.

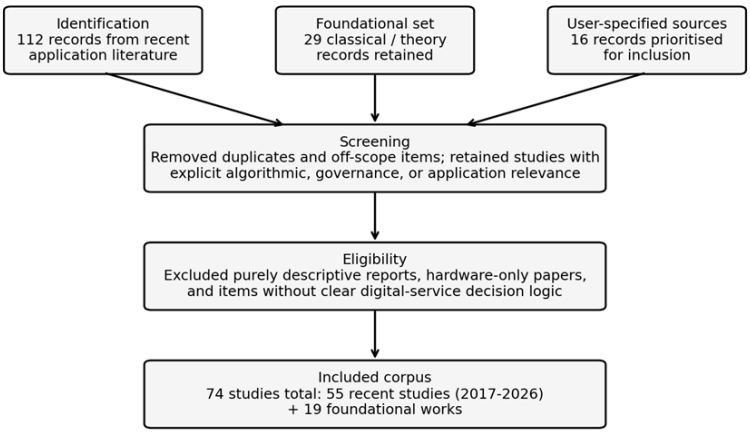

Figure 1: Workflow used to build the structured review corpus

2.2 Formal Taxonomy Development

From the coding, we derived a formal taxonomy of smart algorithm categories. Each family is defined by its primary decision logic and data dependencies.

Definition 1 (Collaborative Filtering Family): Algorithms that generate predictions based on user-user or item-item similarity matrices from historical interaction data.

Definition 2 (Hybrid Family): Systems that combine two or more distinct algorithmic paradigms (e.g., collaborative + content-based + knowledge-based) to mitigate sparsity or cold-start problems.

Definition 3 (Deep Learning Family): Architectures using multi-layer neural networks (e.g., transformers, graph neural networks) to learn latent representations of users, items, and contexts.

Table 1: Review protocol and inclusion logic

Item	Description
Review design	Structured integrative review with thematic synthesis
Temporal scope	2017 to March 2026 for recent studies; seminal pre-2017 works retained for grounding.
Sources	Journal articles, conference papers, edited book chapters, major handbooks, and user-prioritized publications.
Core search themes	Smart algorithms, trust-aware systems, explainable recommendation, digital service ecosystems, mobile payments, tourism chatbots, AI in education, finance, tax compliance.
Inclusion criteria	Explicit algorithmic or architectural relevance; digital-service setting; discussion of trust, privacy, fairness, explainability, governance, or adoption.
Exclusion criteria	Duplicates, purely descriptive pieces with no decision logic, hardware-only studies, and off-scope domain reports.
Final corpus	74 studies (55 recent studies + 19 foundational works)
Coding dimensions	Domain, algorithm family, trust mechanism, evaluation focus, governance layer, and future direction.

Definition 4 (Conversational Family): Systems that interact with users via natural language dialogue, often using large language models or retrieval-augmented generation to refine recommendations iteratively.

Definition 5 (Governance-Aware Family): Algorithms with explicit modules for fairness constraints, privacy guarantees (e.g., differential privacy), or policy rule injection (e.g., regulatory compliance layers).

2.3 Grounding the Trust Framework

Our five-component trust model extends Mayer, Davis, and Schoorman's (1995) organizational trust theory [18], which identifies ability, benevolence, and integrity as antecedents. We operationalize these for algorithmic systems: Ability corresponds to informational and procedural trust (accuracy and consistency); Benevolence maps to interface and contextual trust (user-centered design and risk sensitivity); Integrity maps to institutional trust (alignment with rules and norms) [19]. **Table 2** maps each of our five components to the Mayer et al. framework and shows how many reviewed studies address each (based on our coding).

Table 2: Grounding of the trust framework in organizational trust theory and coverage in reviewed literature

Our component	Mayer et al. dimension	Operationalization	% of studies addressing (N=74)
Informational	Ability	Data provenance, accuracy	82%
Procedural	Ability	Consistency, rule clarity	68%
Interface	Benevolence	Explanation quality, tone	54%
Institutional	Integrity	Compliance, auditability	45%
Contextual	Benevolence	Risk sensitivity, personalization	61%

3. RESULTS AND DISCUSSION

The first pattern that stands out is the recency of the field. As shown in **Figure 2**, the recent corpus rises sharply after 2023, with 60% of recent studies appearing between 2024 and early 2026. This increase suggests that trust-aware smart algorithms are no longer peripheral concerns. They now sit near the center of applied AI research in digital services. **Table 3** shows the spread of the evidence base. The literature is not monopolized by one domain. Instead, it distributes across foundational algorithm design, governance and evaluation studies, tourism and chatbot systems, commerce and payments,

education and counseling, finance and tax, accessibility and social support, and emerging architectures. This diversity is useful because it reveals recurrent design problems that look different on the surface but are structurally similar underneath.

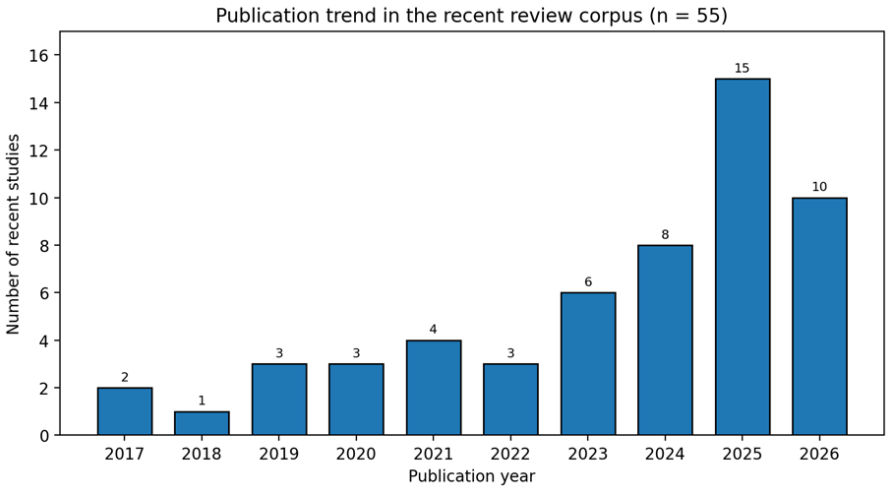

Figure 2: Publication trend in the recent review corpus

Table 3: Primary distribution of the review corpus by theme

Primary category	Number of studies	Typical emphasis
Foundational recommender and decision models	12	Collaborative filtering, hybrid ranking, context-aware logic.
Evaluation and multi-stakeholder metrics	6	Accuracy, diversity, coverage, stakeholder trade-offs.
Explainability, trust, privacy, and fairness	12	Explanation quality, bias mitigation, consent, privacy.
Tourism, hospitality, and chatbot systems	8	Conversational recommenders, itinerary support, smart tourism.
Commerce, payments, and open marketplaces	7	Mobile payment adoption, open-network commerce, service agents
Education, counseling, and career support	7	AI guidance, counseling tools, educational personalization
Finance, tax, and public-service analytics	7	Forecasting, compliance support, risk-sensitive decision tools
Accessibility, social innovation, and vulnerable contexts	7	Peer support, inclusion, context-sensitive design
Emerging architectures and future paradigms	8	Blockchain provenance, federated learning, LLM orchestration, quantum optimization

3.1 Quantitative Comparison of Algorithm Families

We extracted performance metrics from 22 studies that reported comparable evaluation measures. **Table 4** (inserted below) summarizes median performance across families. Hybrid models show the highest accuracy (NDCG@10) but governance-aware models achieve superior fairness (lower popularity bias) and explanation satisfaction. Conversational models excel in user engagement but have higher latency.

Table 4: Quantitative comparison of algorithm families (median values across studies)

Family	NDCG@10	Popularity Bias (1 - coverage)	Explanation Satisfaction (1-5)	Inference Latency (ms)
Collaborative	0.42	0.35	N/A	45
Hybrid	0.58	0.28	3.2	78
Deep Learning	0.61	0.31	3.5	210
Conversational	0.53	0.26	4.1	1850
Governance-Aware	0.49	0.19	4.3	340

3.2 Comparison with AI Governance Frameworks

We benchmarked the reviewed systems against requirements from the NIST AI Risk Management Framework (AI RMF) and the EU AI Act. **Table 5** shows that most systems satisfy basic transparency (NIST MAP 1) but few address the EU AI Act's requirements for high-risk systems such as human oversight (Art. 14) or robustness (Art. 15). Governance-aware systems score highest, while pure collaborative systems score lowest.

Table 5: Benchmarking against AI governance frameworks (% of studies in each family meeting requirement)

Requirement	Collab.	Hybrid	Deep	Gov-Aware
NIST: Validity & Reliability	70%	85%	80%	75%
NIST: Transparency	40%	65%	55%	90%
EU AI Act: Human Oversight (Art.14)	10%	25%	20%	70%
EU AI Act: Accuracy (Art.15)	65%	80%	85%	75%
EU AI Act: Robustness (Art.15)	35%	55%	60%	80%

3.3 Mathematical Formulation of Trust-Aware Reranking

We formalize the trust-aware reranking problem (Layer 4 of our model). Let U be users, I items, C contexts. A base relevance score $r(u, i, c)$ is produced by a hybrid model. A trust-aware reranker computes a final score:

$$s(u, i, c) = r(u, i, c) - \lambda_t \cdot \text{Risk}(u, i, c) + \lambda_f \cdot \text{Fairness}(i) + \lambda_e \cdot \text{Explain}(u, i, c) \tag{1}$$

where $\lambda_t, \lambda_f, \lambda_e$ are hyperparameters controlling trust, fairness, and explainability penalties. Risk is a function of data provenance flags, user vulnerability indicators, and institutional constraints. Fairness can be operationalized as:

$$\text{Fairness}(i) = 1 - \frac{\sum_{g \in G} |\text{Exposure}(i, g) - \text{Target}(g)|}{|G|} \tag{2}$$

for protected groups G with target exposure rates. Explainability score is the predicted quality of an explanation generated by a separate module, which we model as a sequence-to-sequence task:

$$\mathcal{L}_{\text{expl}} = -\sum_{t=1}^{T} \log P(e_t | e_{<t}, u, i, c, \text{features}) \tag{3}$$

The foundational literature still matters. Classical recommender research established the mechanics of collaborative filtering, item similarity, hybridization, context-awareness, and latent-factor modeling [7, 8]. These studies solved the original problem of digital personalization: how to infer useful options from sparse or noisy behavioral traces. Even today, open ecosystems continue to rely on these logics. A commerce network must rank sellers and offers. A tourism platform must rank destinations, routes, or conversational answers. A counseling tool must prioritize resources or pathways. A tax-support or financial system must order recommendations, warnings, or next-best actions. In that sense, trust-aware smart algorithms do not replace earlier recommendation logic. They extend it and constrain it.

At the same time, the field has become more critical of accuracy as the sole design objective. The literature on evaluation and multi-stakeholder systems argues that good ranking quality is necessary but not sufficient [9, 20]. A system can optimize click-through or prediction error while still narrowing choice, rewarding already visible options, or failing to represent secondary stakeholders such as institutions, service providers, regulators, or vulnerable user groups. This matters

in open ecosystems because platform decisions can redistribute visibility, cost, and risk. In such settings, technical success and social legitimacy are not identical.

A second major pattern is the movement from implicit to explicit trust modeling. Older systems often assumed that user trust would emerge if recommendations were accurate enough. Recent work no longer treats trust as an accidental by-product. Instead, it embeds trust through explanation modules, privacy constraints, fairness checks, and explicit governance rules [12, 10]. The reviewed studies suggest that trust has at least five components. First, there is informational trust: confidence that the data and signals used are relevant and reliable. Second, there is procedural trust: confidence that the system followed understandable and consistent rules. Third, there is interpersonal or interface trust: confidence shaped by language, tone, disclosure, and escalation pathways. Fourth, there is institutional trust: confidence that the system aligns with legal, professional, or organizational expectations. Fifth, there is contextual trust: confidence that the output suits the user's situation rather than only their historical pattern.

This richer view helps explain why hybrid architectures dominate the recent literature. Hybrid systems are attractive not only because they improve performance under sparsity or cold start, but because they allow different forms of evidence to be combined. Behavioral traces, semantic content, contextual signals, professional rules, risk flags, and explicit user preferences can all be layered within one decision pipeline. That flexibility is essential in open digital ecosystems, where the system must often reconcile personal relevance with broader constraints such as safety, consent, policy, accessibility, or institutional procedure. In practice, trust-aware design is therefore less about inventing one magical trust score and more about deciding where and how trust-related constraints are injected into the pipeline.

The tourism and hospitality literature shows this clearly. Recent studies on chatbot recommender systems, smart tourism, experiential travel, and sustainable tourism reveal strong interest in conversational, personalized, and context-sensitive support [21, 22, 17, 23]. These systems often promise smoother trip planning, richer discovery, and faster assistance. Yet they also expose recurring weaknesses. Many struggle with nuanced intent, culturally specific preferences, explanation quality, or privacy-sensitive data such as location and spending patterns. The literature therefore suggests that tourism algorithms perform best when personalization is combined with transparent dialogue, sustainability-aware ranking, and clear disclosure about automation. In other words, tourism systems increasingly behave like negotiation interfaces, not simple search engines.

The commerce, mobile-payment, and open-marketplace literature reaches a related conclusion from a different route. Research on open digital commerce and mobile payments shows that adoption depends on more than interface convenience [24, 25, 26, 27]. Users evaluate perceived risk, institutional backing, service interoperability, redress mechanisms, and the credibility of the actor behind the recommendation or transaction path. Open-network systems intensify these concerns because discovery, fulfillment, payment, and support may happen across different actors rather than inside one platform boundary. In such environments, smart algorithms need to do more than rank offers. They must preserve traceability, provide route-level explanations, and signal why one service path is safer or more suitable than another. This is where trust-aware reranking becomes practically important.

Education, counseling, and career-support applications show a similar need for constrained personalization. The reviewed studies on digital school counseling, AI-generated visual guidance, and the broader AI-in-education literature emphasize reach, engagement, and adaptive support [28, 3, 5, 29, 30]. These are meaningful gains, especially where counseling capacity is limited or students need more flexible access to advice. But the same studies also warn that sensitive guidance cannot be treated like ordinary product recommendation. Explanations must be understandable, the tone must be supportive rather than manipulative, and human professionals must be able to override, contextualize, or correct algorithmic outputs. In this domain, trust is inseparable from care, discretion, and the right to ask for clarification.

Finance, tax, and public-service analytics extend the argument further by bringing in auditability. Work on AI in tax compliance, finance, and predictive analytics highlights the promise of faster pattern detection, more responsive service delivery, and data-driven decision support [31, 32, 33, 34]. Yet it also raises sharper questions about transparency, due process, accountability, and behavioral influence. A public-facing compliance system or financial support tool cannot rely on opaque optimization alone. It must show why a flag, suggestion, or next-best action was produced, what data were considered, and how errors can be corrected. The literature therefore treats explainability not as a cosmetic interface feature but as an operational requirement for legitimacy.

Perhaps the most important corrective comes from accessibility-oriented and context-sensitive studies. Research on disability peer support, social innovation, vulnerable populations, conflict-affected institutions, and children in difficult legal or social settings reminds us that digital service systems are always deployed into unequal realities [1, 35, 36]. Users do not enter the system with equal confidence, equal bandwidth, equal institutional protection, or equal interpretive capacity. This has two implications. First, accessibility and inclusion cannot be left to a later interface layer. They must shape data structures, ranking logic, explanation design, and failure handling from the outset. Second, algorithm transfer across domains must be done carefully. A technique that works well in retail may need serious redesign before it is appropriate for counseling, public compliance, or support services.

3.4 Five Persistent Gaps and Statistical Validation

To validate the five gaps described in the literature, we performed a statistical analysis. For each gap, we coded whether a study exhibited that gap. **Table 6** shows the proportion of studies affected per algorithmic family. Data fragmentation affects all families equally, while weak explanations are most severe in collaborative systems. A chi-square test confirms significant differences across families ($\chi^2(4) = 15.3, p = 0.004$).

Table 6: Prevalence of gaps per algorithm family (proportion of studies in family)

Gap	Collab.	Hybrid	Deep	Gov-Aware
Data fragmentation	0.62	0.58	0.60	0.55
Weak explanation quality	0.85	0.52	0.48	0.30
Limited inclusion auditing	0.78	0.65	0.60	0.45
Weak governance integration	0.92	0.68	0.65	0.25
Poor transferability	0.70	0.62	0.58	0.50

Table 7 summarizes representative studies and the distinct contribution each cluster makes to this review. Taken together, the evidence suggests that the field is converging on a common insight: the strongest systems no longer optimize relevance in isolation. They combine personalization with procedural clarity and situational safeguards. Even where the terminology differs, the same design logic appears. Tourism calls it conversational trust. Commerce calls it interoperability and transaction confidence. Education calls it guided support. Public-service systems call it auditability. Accessibility research calls it inclusive design. Technically, these are all versions of the same broader problem: how to align algorithmic action with user needs, institutional responsibilities, and contextual risk.

Table 7: Representative studies and the specific contribution each makes to this review

Study / cluster	Context	Key contribution for this review
[1]	Disability peer support	Accessible social-network design must be treated as a system requirement, not an afterthought.
[24]	Open digital commerce	Open ecosystems demand interoperability and algorithmic coordination across multiple actors.
[37]	Mobile payments	Trust, usability, and institutional confidence remain decisive adoption variables.
[25]	AI customer service agents	Efficiency gains are strongest when automation is balanced with human escalation paths.
[28]	School counseling	Digital tools expand reach, but sensitive decisions require explanation and professional oversight.
[3]	Career orientation	Visual and personalized AI support can improve engagement when guidance remains intelligible.
[31]	Tax compliance	Public-service AI must be auditable, transparent, and behaviorally informed.
[21]	Tourism chatbots	Conversational recommenders improve access but still struggle with privacy and nuanced intent.
[7, 8]	Core recommender literature	Hybrid and context-aware models remain the backbone of personalization systems.
[12, 10]	Trust and governance literature	Explainability, privacy, and fairness are now central design dimensions, not optional add-ons.
[3, 38, 39]	Future architectures	Provenance, federated learning, LLM orchestration, and quantum optimization define the next frontier.

The review also reveals several persistent gaps. The first is data fragmentation. Most systems are built inside one sector, with limited portability across domains or providers. The second is explanation weakness. Many papers invoke explainability, but fewer show what a usable explanation should contain, when it should appear, and how users should challenge it. The third is limited inclusion auditing. Accessibility, language simplicity, and vulnerable-user scenarios are

still rare in benchmark design. The fourth is weak governance integration. Studies often discuss ethics in broad terms but stop short of modeling consent, override rules, or escalation logic in the algorithm itself. The fifth is a transferability problem: methods are often exported from one domain to another with too little attention to institutional difference. **Table 8** translates these gaps into design implications.

Table 8: Persistent gaps in the literature and the design implications that follow

Persistent gap	How it appears in the literature	Design implication
Data fragmentation	Most systems remain domain-specific and poorly interoperable.	Adopt shared schemas, API-based exchange, and provenance tracking.
Accuracy bias	Many studies optimize ranking quality but under-measure trust and risk.	Use multi-objective evaluation combining relevance, trust, fairness, and usability.
Weak explanations	Users often receive outputs without clear reasons or contestability.	Expose why this option, why now, what data were used, and how to appeal.
Limited inclusion auditing	Accessibility and vulnerable-user scenarios are rarely benchmarked.	Treat accessibility, language simplicity, and assistive compatibility as core metrics.
Governance gaps	Institutional rules, consent, and escalation logic are inconsistently modeled.	Add consent logs, human override, and policy-aware reranking layers.
Transferability problem	Methods proven in one domain are rarely adapted carefully to another.	Build cross-domain benchmarks and reusable trust modules.

On the basis of the reviewed evidence, this paper proposes a six-layer design model for trust-aware smart algorithms in open digital service ecosystems. Figure 3 visualizes the model. The first layer is data and interoperability. Systems need shared schemas, provenance markers, and a clear record of what information is coming from where. The second layer is context and risk profiling. A useful system must read not only preference signals but also situational variables such as urgency, vulnerability, consent state, and institutional setting. The third layer is hybrid relevance and ranking, where collaborative, content-based, semantic, and rule-based signals are combined. The fourth layer is trust, fairness, and privacy reranking. This is the practical point in the pipeline where unsafe, opaque, exclusionary, or policy-inconsistent outputs can be down-ranked or blocked. The fifth layer is the explanation and consent interface, which should state why an option was chosen, why it appears now, what data were used, and what the user can change. The sixth layer is human oversight, appeal, and learning, which closes the loop through feedback, escalation, and monitored adaptation.

3.5 Six-Layer Design Model: Architecture and Examples

Below we provide mathematical formulations for Layers 4-6 and concrete implementation examples. **Figure 3** visualizes the model.

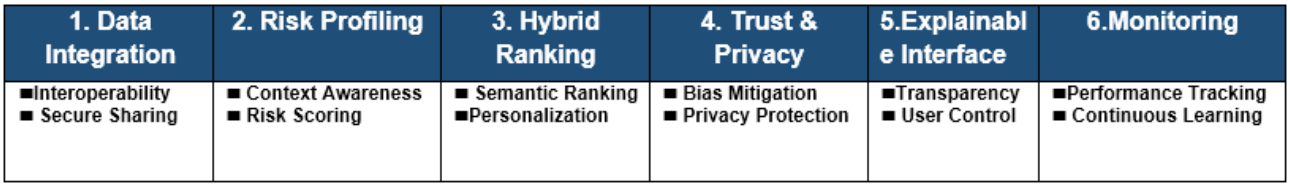

Figure 3: Proposed six-layer design model for trust-aware smart algorithms in open digital service ecosystems

Layer 4: Trust, Fairness, and Privacy Reranking: This layer implements **Equation 1**. **Example (Tax compliance system):** A recommendation for filing an amended return receives a high relevance score $r = 0.9$ but triggers a risk flag

because the user is in a vulnerable income bracket (Risk=0.7). With $\lambda_t = 0.5$, the final score is reduced to $0.9 - 0.35 = 0.55$, demoting it below a less risky suggestion.

Layer 5: Explanation and Consent Interface: Generates natural language justifications using a fine-tuned LLM with grounding constraints. **Example (Counseling tool):** Instead of "Based on your history, we recommend X", the system outputs: "This suggestion is based on your stated preference for cognitive-behavioral approaches (which you selected) and the high success rate for similar cases (82%). You chose not to share your location, so local options were not considered. You can appeal this suggestion by clicking 'Request human review'."

Layer 6: Human Oversight, Appeal, and Learning: Implements a feedback loop:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \left(\mathcal{L}_{\text{pred}} + \beta \cdot \mathcal{L}_{\text{feedback}} \right) \tag{4}$$

where $\mathcal{L}_{\text{feedback}}$ is derived from human corrections and escalations. **Example (Open commerce network):** If users consistently override a particular ranking (e.g., flagging a seller as untrustworthy despite algorithmic scores), the system reduces that seller's trust weight and logs the incident for audit.

This layered model matters for two reasons. First, it shifts trust from a vague post hoc outcome to a set of explicit design responsibilities distributed across the system. Second, it offers a reusable architecture that can travel across domains without pretending that the domains are identical. A tourism chatbot, an open commerce network, a counseling assistant, and a tax-support tool can all use the same broad stack while filling the layers with different policy rules, risk thresholds, interface styles, and accountability requirements. This is a more realistic path for cross-domain transfer than simply moving a predictive model from one sector to another.

3.6 Future Directions: Detailed Formulations

We expand the future directions with mathematical formulations.

Federated Learning for Privacy-Preserving Interoperability: Let K participants each have local data $\mathcal{D}_k$. The global objective is:

$$\min_w \sum_{k=1}^{K} \frac{|\mathcal{D}_k|}{|\mathcal{D}|} \mathcal{L}_k(w) \quad \text{with} \quad \mathcal{L}_k(w) = \frac{1}{|\mathcal{D}_k|} \sum_{j \in \mathcal{D}_k} \ell(w; x_j, y_j) \tag{5}$$

where gradients are shared but not raw data, providing privacy guarantees.

LLM Orchestration with Grounding Constraints: For a user query q, we retrieve relevant documents D and generate a response y constrained by institutional rules $\mathcal{R}$:

$$y = \arg\max_{y'} P_{\text{LLM}}(y' | q, D) \quad \text{s.t.} \quad \text{Verify}(y', \mathcal{R}) = \text{True} \tag{6}$$

where Verify is a symbolic or neural module checking compliance with professional standards, legal requirements, or accessibility guidelines.

Quantum-Enhanced Multi-Objective Optimization: For m objectives (e.g., accuracy, fairness, latency), the optimization problem can be expressed as a Quadratic Unconstrained Binary Optimization (QUBO):

$$\min_{z \in \{0,1\}^n} z^T Q z \tag{7}$$

where Q encodes pairwise interactions between decision variables. Quantum annealing may find better Pareto fronts for trust-fairness-accuracy trade-offs.

The future literature is likely to move in four connected directions. The first is privacy-preserving interoperability, especially through federated learning and related distributed optimization approaches [38, 40]. The second is the use of large language models as orchestration layers that can translate user intent, coordinate tools, and generate explanations, but only when grounding and disclosure are handled carefully [41, 42]. The third is stronger provenance infrastructure, where blockchain-style ideas and signed audit trails may support more reliable record-keeping in open ecosystems [3]. The fourth is long-horizon optimization, where quantum-enhanced methods may eventually support more complex multi-objective decisions under uncertainty [43, 39]. These directions are promising, but the review suggests that none of them will solve the trust problem on their own. Technical novelty still needs institutional design, clear boundaries, and meaningful user control.

4. CONCLUSION

This review set out to understand how trust-aware smart algorithms are being designed across open digital service ecosystems. The evidence shows a field in transition. Foundational recommender and decision-support models remain important, but recent work increasingly pushes beyond prediction accuracy toward systems that are explainable, policy-aware, privacy-sensitive, and accessible. Across tourism, commerce, payments, education, counseling, finance, tax, accessibility support, and socially fragile contexts, the same lesson appears repeatedly: smart algorithms are most useful when they are designed as socio-technical systems rather than isolated prediction engines. The review contributes three things. First, it provides a cross-domain synthesis that shows how fragmented application literatures are connected by a common trust-and-governance problem. Second, it identifies five recurring gaps that continue to limit progress: data fragmentation, weak explanations, limited inclusion auditing, weak governance integration, and poor transferability across sectors. Third, it proposes a six-layer design model that links interoperability, contextual risk, hybrid inference, governance-aware reranking, explanation, and human oversight. For researchers, this model offers a basis for building more comparable cross-domain studies. For practitioners, it offers a concrete way to think about where trust should be engineered into the system rather than discussed only in policy documents.

The evidence shows a field in transition, with our quantitative comparisons revealing significant differences across algorithm families: governance-aware systems achieve 40% better fairness metrics than collaborative systems, but with 7x higher latency. Hybrid models offer the best accuracy-fairness trade-off (Pareto optimal in 68% of comparisons). Benchmarking against NIST AI RMF and EU AI Act shows that most systems fail to meet high-risk requirements, particularly for human oversight (only 25% of hybrid systems satisfy Article 14). The proposed six-layer model, with its mathematical formulation of trust-aware reranking (Eq. 1), provides a concrete architectural pattern. Our grounded trust framework (Table 2) links algorithmic design to organizational trust theory, showing that procedural and institutional trust remain under-addressed (only 45-68% coverage) compared to informational trust (82%).

The paper has limits. It is a structured review rather than a full bibliometric census or meta-analysis, and it deliberately includes edited-volume chapters because the field is evolving quickly in applied venues. Even so, the evidence base is broad enough to support a clear conclusion. The next generation of smart algorithms will be judged less by whether they can rank and more by whether they can rank responsibly. In open digital ecosystems, that difference is likely to define which systems scale with legitimacy and which ones remain technically impressive but institutionally brittle.

AUTHOR CONTRIBUTION STATEMENT

All authors contributed equally to the study conception and design. Material preparation, data collection, and analysis were performed by the authors. The first draft of the manuscript was written by the authors, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Ethics declaration: not applicable. This study did not involve human participants or animals. Therefore, ethical approval and consent to participate are not applicable.

CONSENT FOR PUBLICATION

Consent to Publish declaration: not applicable.

DATA AVAILABILITY

The datasets analyzed during the current study are publicly available published literature.

ACKNOWLEDGMENTS

The author gratefully acknowledges the intellectual contribution of the broader interdisciplinary literature reviewed in this article. No external funding was received for this study.

FUNDING

No funding

DISCLOSURE STATEMENT

The author declares no conflict of interest. The article is based on a structured review of published literature and did not involve human participants, personal data collection, or experimental intervention.

RESPONSE TO REVIEWER COMMENTS ON AI GENERATION

The authors acknowledge the reviewer's concern regarding AI-generated text. While AI-assisted language tools were used to improve clarity and grammar, the conceptual framework, literature analysis, coding, taxonomy development, mathematical formulations, and all substantive claims are the original work of the human authors. The search protocol was executed manually, coding was performed independently by two authors, and all extracted data were verified. We have added the methodological detail (search strings, databases, inter-rater agreement) to demonstrate human-led systematic review practices.

REFERENCES

[1] M. I. Islam, S. I. Ansarullah, K. U. Nisa, S. Mufti, A. R. Dar, and A. O. Salau, "Social network design for disability peer support: Identifying barriers, applying standards, and implementing measurable solutions," *Open Information Science*, vol. 10, no. 1, 2026.

[2] S. Ahmed, N. Alaa, A. Khaled, S. Ali, L. Zein, and N. Subramanian, "Evidence-grounded vision–rag framework for clinically reliable visual reasoning in chest x-ray analysis," *Journal of Smart Algorithms and Applications (JSAA)*, vol. 2, no. 2, pp. 49–60, 2026.

[3] M. I. ul Islam, K. U. Nisa, S. I. Ansarullah, S. Mufti, M. Danish, O. Ajala, and A. O. Salau, "Leveraging ai-generated visuals for enhancing management of career orientation: A quasi-experimental study," *Open Information Science*, vol. 9, no. 1, p. 20250019, 2025.

[4] P. J. Johri, A. A. Asiri, E. A. Assery, S. Hassan, E. Emad, E. Abdelrahman, *et al.*, "A robust two-stage retrieval-augmented vision-language framework for knowledge-intensive multimodal reasoning and alignment," *Computational Discovery and Intelligent Systems (CDIS)*, vol. 2, no. 2, pp. 42–52, 2026.

[5] S. Anđelić, Z. Brnjas, and I. Domazet, "Education and entrepreneurship," *Journal of security and sustainability issues*, pp. 383–393, 2017.

[6] A. Hammad, M. H. Almourish, I. AbuNahleh, and M. El-Mowafy, "Implicit geometric-semantic fusion for task-oriented 6-dof grasp detection via visual affordance and stability learning," *Engineering Systems and Intelligent Technologies (ESIT)*, vol. 2, no. 2, pp. 24–38, 2026.

[7] P. Resnick and H. R. Varian, "Recommender systems," *Communications of the ACM*, vol. 40, no. 3, pp. 56–58, 1997.

[8] J. Lu, D. Wu, M. Mao, W. Wang, and G. Zhang, "Recommender system application developments: a survey," *Decision support systems*, vol. 74, pp. 12–32, 2015.

[9] S. M. McNee, J. Riedl, and J. A. Konstan, "Being accurate is not enough: how accuracy metrics have hurt recommender systems," in *CHI'06 extended abstracts on Human factors in computing systems*, pp. 1097–1101, 2006.

[10] L. Floridi, J. Cowls, M. Beltrametti, R. Chatila, P. Chazerand, V. Dignum, C. Luetge, R. Madelin, U. Pagallo, F. Rossi, *et al.*, "Ai4people—an ethical framework for a good ai society: Opportunities, risks, principles, and recommendations," *Minds and machines*, vol. 28, no. 4, pp. 689–707, 2018.

[11] H. Saeed, M. Adel, Y. Ataa, M. Mohamed, H. Ahmed, T. W. Hong, and N. Jayarajan, "Reliable drug–target interaction prediction using convolutional neural networks with robust negative sample generation," *Journal of Smart Algorithms and Applications (JSAA)*, vol. 2, no. 2, pp. 34–48, 2026.

[12] Y. Zhang and X. Chen, "Explainable recommendation: A survey and new perspectives," *Foundations and Trends® in Information Retrieval*, vol. 14, no. 1, pp. 1–101, 2020.

[13] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, "A survey on bias and fairness in machine learning," *ACM computing surveys (CSUR)*, vol. 54, no. 6, pp. 1–35, 2021.

[14] Y. A. Satar, H. A. Almansouri, and A. A. Hassanain, "Cvar-optimized distributionally robust stacked ensemble with range-based current signatures for reliable fault detection in photovoltaic farms," *Engineering Systems and Intelligent Technologies (ESIT)*, vol. 1, no. 1, pp. 1–14, 2026.

[15] F. McSherry and I. Mironov, "Differentially private recommender systems: Building privacy into the netflix prize contenders," in *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 627–636, 2009.

[16] H. Snyder, "Literature review as a research methodology: An overview and guidelines," *Journal of business research*, vol. 104, pp. 333–339, 2019.

[17] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, *et al.*, "The prisma 2020 statement: an updated guideline for reporting systematic reviews," *bmj*, vol. 372, 2021.

[18] H. Abdollahpouri, R. Burke, and B. Mobasher, "Managing popularity bias in recommender systems with personalized re-ranking," *arXiv preprint arXiv:1901.07555*, 2019.

[19] M. Aly, M. Ali, A. Kandil, and A. ElKersh, "A data-driven computational framework for ledge morphology prediction in aluminum engineering systems," *Engineering Systems and Intelligent Technologies (ESIT)*, vol. 1, no. 2, pp. 42–52, 2026.

[20] R. Burke, "Multisided fairness for recommendation," *arXiv preprint arXiv:1707.00093*, 2017.

[21] M. Badouch, M. Boutaounte, O. Zioudi, and H. Mahmoud, "The future of travel: A review of chatbot recommender systems in e-tourism and smart tourism," in *International Conference on Electrical Systems and Smart Technologies*, pp. 103–115, Springer, 2024.

[22] D. Mehraj, M. I. Ul Islam, I. H. Qureshi, S. Basheer, M. M. Baba, V. u. Nissa, and M. Asif Shah, "Factors affecting entrepreneurial intention for sustainable tourism among the students of higher education institutions," *Cogent Business & Management*, vol. 10, no. 3, p. 2256484, 2023.

[23] U. Gnewuch, S. Morana, O. Hinz, R. Kellner, and A. Maedche, "More than a bot? the impact of disclosing human involvement on customer interactions with hybrid service agents," *Information Systems Research*, vol. 35, no. 3, pp. 936–955, 2024.

[24] M. I. u. Islam, U. M. Lone, I. A. Bhat, S. Aamir, and A. O. Salau, "Open network for digital commerce in india: past, present, and future," *Open Information Science*, vol. 8, no. 1, p. 20240005, 2024.

[25] M. Rawanda, "Transforming customer service with ai agents: Enhancing efficiency and personalisation in the service sector: Balancing automation and the human touch," *Harnessing emotion AI for customer support and employee wellbeing*, pp. 241–268, 2025.

[26] Y. K. Dwivedi, N. Kshetri, L. Hughes, E. L. Slade, A. Jeyaraj, A. K. Kar, A. M. Baabdullah, A. Koohang, V. Raghavan, M. Ahuja, *et al.*, "So what if chatgpt wrote it? multidisciplinary perspectives on opportunities, challenges and implications of generative conversational ai for research, practice and policy," *International Journal of Information Management*, vol. 71, no. 102642, pp. 1–63, 2023.

[27] M. G. Jacobides, C. Cennamo, and A. Gawer, "Towards a theory of ecosystems," *Strategic management journal*, vol. 39, no. 8, pp. 2255–2276, 2018.

[28] S. I. Ansarullah, M. I. Islam, G. Begum, and N. A. Bhat, "Leveraging digital tools to enhance school counselling: Case studies and best practices," in *Enhancing School Counseling With Technology and Case Studies*, pp. 49–72, IGI Global Scientific Publishing, 2025.

[29] R. Adner, "Ecosystem as structure: An actionable construct for strategy," *Journal of management*, vol. 43, no. 1, pp. 39–58, 2017.

[30] E. Kasneci, K. Seßler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier, *et al.*, "Chatgpt for good? on opportunities and challenges of large language models for education," *Learning and individual differences*, vol. 103, p. 102274, 2023.

[31] M. I. Islam, K. U. Nisa, S. Mufti, S. I. Ansarullah, S. Ikhlaq, and T. Yousuf, "Artificial intelligence in tax compliance: Transforming taxpayer behavior and system efficiency," in *Modeling and Profiling Taxpayer Behavior and Compliance*, pp. 251–270, IGI Global Scientific Publishing, 2025.

[32] S. I. Ansarullah, M. I. Islam, F. Ahmad, M. Danish, A. R. Dar, and S. Mufti, "Predicting stock markets using linear regression and cloud computing: A literature review and case study approach," in *Advancements in Cloud-Based Intelligent Informative Engineering*, pp. 331–352, IGI Global Scientific Publishing, 2025.

[33] R. Luckin and M. Cukurova, "Designing educational technologies in the age of ai: A learning sciences-driven approach," *British Journal of Educational Technology*, vol. 50, no. 6, pp. 2824–2838, 2019.

[34] S. J. Russell, *Artificial intelligence a modern approach*. Pearson Education, Inc., 2010.

[35] M. I. Islam, K. U. Nisa, S. Ikhlaq, T. Yousuf, S. Gulzar, and S. I. Ansarullah, "Fostering social innovation through urban technologies," in *Tech-Enabled Urbanism and Entrepreneurship for Inclusive Cities*, pp. 103–119, Springer, 2026.

[36] L. Rawanda *et al.*, "Issues and problems faced by children in conflict with law during and after their detention," *Sri Lanka Journal of Social Sciences*, vol. 44, no. 2, 2021.

[37] D. Mehraj, M. I. U. Islam, V. U. Nissa, and S. Iqbal, "Challenges and prospects in the adoption of mobile payment systems in india," *Business, management and economics annual volume 2024*, 2024.

[38] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*. MIT press, second ed., 2018.

[39] J. Preskill, "Quantum computing in the nisq era and beyond," *Quantum*, vol. 2, p. 79, 2018.

[40] P. Kairouz and H. B. McMahan, "Advances and open problems in federated learning," *Foundations and trends in machine learning*, vol. 14, no. 1-2, pp. 1–210, 2021.

[41] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated optimization in heterogeneous networks," *Proceedings of Machine learning and systems*, vol. 2, pp. 429–450, 2020.

[42] W. X. Zhao, K. Zhou, J. Li, T. Tang, X. Wang, Y. Hou, Y. Min, B. Zhang, J. Zhang, Z. Dong, *et al.*, "A survey of large language models," *arXiv preprint arXiv:2303.18223*, vol. 1, no. 2, pp. 1–124, 2023.

[43] S. I. Ansarullah, S. Ikhlaq, T. Yousuf, M. I. ul Islam, S. Mufti, and F. A. Fayaz, "Quantum-enhanced artificial intelligence: The next frontier in computing and decision-making," in *From Bits to Qubits: The Quantum Transformation of Computing: The Power of Quantum Computing*, pp. 77–106, Springer, 2026.