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Systematic Review

Real Estate Recommender Systems: A PRISMA-Compliant Systematic Review of Multimodal, Spatio-Temporal, Explainable, and Fairness-Aware Innovations

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Abstract

The rapid expansion of online real estate (RE) platforms has intensified information overload, making property search and decision-making increasingly complex. Real estate recommendation systems (RERSs) have emerged as essential decision-support tools; however, their development has not kept pace with advances in explainable artificial intelligence (XAI), transfer learning (TL), and fairness-aware machine learning. This PRISMA-compliant systematic review synthesizes 59 peer-reviewed studies published between 2005 and 2025 to critically examine algorithmic approaches, data modalities, evaluation practices, and ethical considerations in RERS research. Our analysis reveals a substantial lag in the adoption of state-of-the-art AI techniques: While deep learning is employed in 15% of studies, no reviewed work implements state-of-the-art post hoc XAI or TL frameworks, despite their relevance for addressing interpretability and data scarcity challenges. Furthermore, we identify systemic research biases, including reliance on proprietary datasets (80%), geographic concentration in Asia (56%), the dominance of residential property studies (91%), and limited fairness auditing despite documented discrimination risks in housing markets. To address these gaps, we propose a trust-based evaluation (T-EVAL) framework that integrates predictive accuracy, user trust, fairness, and market efficiency, and introduces a comprehensive nine-layer conceptual architecture for transparent, ethical, and data-efficient next-generation RERS. This review establishes an empirical benchmark for technology adoption gaps and outlines a research agenda for advancing responsible AI in RE decision-support systems.

Keywords: real estate; recommender systems; transfer learning; explainable AI; fairness; multimodal fusion

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1. Introduction

RERSs address the fundamental challenge of navigating high-stakes, infrequent decisions in dynamic property markets worth $393 trillion globally [1]. Given this high value, the efficiency and fairness of recommendation algorithms have profound macroeconomic implications. These recommendation systems reduce information overload by personalizing recommendations based on user preferences, property attributes, and contextual factors such as market trends and neighborhood dynamics. However, despite the domain's economic significance, RE accounts for 59% of global conventional resources [2]. RERSs

are a growing and nascent field regarding the integration of ethical and spatio-temporal dimensions in the academic literature, despite the inherent complexities of the domain, including unstructured data (such as text, images, and geospatial information), the cold-start problem for new users and listings, and the market's temporal nature [3]. The development of RERS remains fragmented, with persistent challenges including data sparsity, limited interpretability, and algorithmic bias.

1.1. Critical Review of Existing Surveys and Research Gaps in RERS

Recent systematic reviews have documented the evolution of RERS, from traditional collaborative filtering (CF) and content-based (CB) approaches toward hybrid and deep learning (DL) models. These reviews have provided valuable taxonomies and identified challenges such as cold-start, data sparsity, and scalability. However, they remain limited in scope and depth when benchmarked against contemporary advances in artificial intelligence (AI) and responsible AI frameworks. Table 1 summarizes key peer-reviewed review studies on RERSs and their coverage of advanced AI technologies.

Table 1. Themes from some reviewed articles motivating this study.

Reference	Key Focus Areas	Coverage of Advanced Technologies (DL, Natural Language Processing (NLP), TL, Multimodal Fusion, XAI)
[4]	Early RERS using CB and CF; focus on user profiling and preference elicitation.	No coverage of DL, NLP, TL, multimodal fusion, or XAI.
[5]	CB, CF, and knowledge-based systems; cold-start and scalability issues.	Minimal discussion of early ML; no coverage of DL, NLP, TL, multimodal fusion, or XAI.
[6]	Applications of CB, CF, and hybrid RERSs; challenges like cold-start and data sparsity.	Limited discussion of DL for feature extraction; brief mention of NLP for user queries; no coverage of TL, multimodal fusion, or XAI.
[2]	CB, CF, KB, and hybrid methods; future research directions.	Mentions DL and NLP applications; suggests TL and multimodal fusion as future directions but lacks in-depth analysis; no discussion of XAI.
[7]	Fuzzy logic for handling uncertainty in user preferences; hybrid RERS.	Partial coverage of DL for property feature analysis; limited NLP for text processing; no coverage of TL, multimodal fusion, or XAI.
[8]	CB, CF, KB, and HB systems; future research directions.	Coverage of DL (CNN, LSTM); suggests for future research the use of TL, XAI, spatio-temporal modeling, and multimodal learning.
[9]	Hierarchical architecture design for personalized RS to address user difficulty in finding houses.	DL (CNN) used in the recommendation layer to generate results.

As shown in Table 1, existing reviews predominantly focus on CF, CB, and hybrid recommender system paradigms, with limited exploration of DL- and NLP-based approaches. The comparative analysis is grounded in high-impact surveys such as [6,8]. These were selected as they represent the most recent efforts to categorize the RE recommendation landscape prior to the development of our multimodal framework. Importantly, none of the reviewed surveys systematically investigates the implementation of multimodal fusion, spatio-temporal modeling, TL, or XAI in RERS. Instead, these techniques are largely discussed as prospective future research directions rather than empirically analyzed research streams.

Beyond technological coverage, prior reviews exhibit several conceptual and methodological limitations. First, there is limited synthesis of multimodal data integration, particularly regarding the fusion of textual descriptions, visual imagery, and geospatial information. Second, there is insufficient analysis of spatio-temporal modeling, despite the inherently dynamic and spatially structured nature of RE markets. Third, there is an absence of systematic evaluation of explainability mechanisms, despite the high-stakes nature of RE decisions involving substantial financial and social implications. Fourth, there is minimal investigation of fairness-aware system design and regulatory compliance, despite documented biases and discrimination risks in housing markets.

More fundamentally, existing reviews employ heterogeneous and often inconsistent methodologies and do not empirically quantify technology adoption gaps. Our preliminary analysis of 59 peer-reviewed studies reveals a striking pattern: While 15% employ DL techniques, 0% implement post hoc XAI methods (e.g., SHAP, LIME), and 0% utilize TL, despite these being established solutions to RERS's core challenges of interpretability and data scarcity. In addition, the framework's validity is demonstrated through categorical coverage. By mapping the 59 core articles in our corpus against the proposed architecture, we confirmed that all existing RERS methodologies, ranging from traditional CF to modern DL approaches, can be situated within these nine layers without structural overlap or omissions.

1.2. Research Objectives and Novel Contributions

This PRISMA-compliant systematic review addresses these gaps through three primary objectives:

RO1: Synthesize advances in algorithms, data modalities, and evaluation practices in RERS, with particular focus on multimodal fusion, spatio-temporal modeling, XAI, and TL adoption;

RO2: Critically appraise the limitations of existing research through quantitative gap analysis, identifying technological, methodological, geographic, and ethical deficiencies;

RO3: Propose evidence-based frameworks for next-generation RERS, including a T-EVAL paradigm and a comprehensive nine-layer conceptual architecture.

Our review makes four novel contributions to RERS:

1. *First empirical documentation* of the XAI/TL adoption gap, quantifying the disconnect between available techniques and deployed solutions;
2. *T-EVAL framework*: A multi-dimensional evaluation paradigm integrating accuracy, user trust, fairness, and market efficiency, thus moving beyond narrow Precision/Recall metrics;
3. *Comprehensive conceptual architecture*: A systematically validated nine-layer framework starting from data ingestion and preprocessing to feature engineering, multimodal fusion, spatio-temporal, TL, model generation, XAI, recommendation, and ending at the user interface. The layers addressing explainability and fairness were validated against the recent requirements proposed by [3] and the systematic gaps identified by [8]. While the proposed nine-layer framework is optimized for property markets, its architectural principles are anchored in the broader pursuit of responsible AI. By integrating layers for XAI and regulation awareness, this review contributes to the global discourse on algorithmic accountability in high-stakes human environments;
4. *Actionable research agenda*: Evidence-based recommendations for addressing the "ecological validity gap" through real-world validation, standardized datasets, and fairness auditing.

1.3. Scope and Justification

This review focuses on the period 2005–2025 to capture the emergence and maturation of DL and data-driven recommender system methodologies while maintaining a manageable and methodologically coherent scope. This period witnessed transformative advances in AI, including convolutional neural networks (CNNs) for image-based feature extraction, long short-term memory (LSTM) networks for temporal modeling, graph neural networks (GNNs) for spatial and relational learning, and transformer architectures for attention-based representation learning. We selected 2005 as the terminus a quo because it marks a paradigm shift in the RE industry: the transition from analog, agent-mediated listings to

digitized data-rich property platforms (Web 2.0). Pre-2005 methods (e.g., rule-based systems and basic matrix factorization) are referenced where foundational but were excluded from systematic synthesis due to their limited relevance to contemporary AI-driven RERS. They lacked the spatio-temporal granularity and multimodal data, e.g., digital imagery and GIS integration, that are foundational to our nine-layer framework. In addition, the specific "high-stakes, low-frequency" nature of property transactions necessitates distinct algorithmic logic that differs from "low-stakes, high-frequency" foundational work that includes movies and e-commerce of the 1990s.

Over the past years, researchers have explored various methods to address challenges in RERS. The cold-start problem has been mitigated using personalized probabilistic relational models that incorporate user preferences such as budget, location, and property [10]. Data scarcity issues have been tackled using hybrid recommender systems that combine CB and CF approaches, leveraging property attributes and user interaction data to improve recommendation quality [11]. Additionally, electronic profiling agents have been utilized to capture user preferences and dynamically enhance personalization in RERS [4].

Despite these advances, most studies continue to rely on traditional CB and CF paradigms to address cold-start and data sparsity challenges. The integration of advanced technologies such as XAI, TL, and multimodal fusion techniques to address RERS challenges remains limited and fragmented. This review, therefore, concentrates on synthesizing and critically evaluating research within this period to identify technological, methodological, and ethical gaps and to outline pathways toward transparent, data-efficient, and responsible RERS.

2. Background: RERS Evolution and Persistent Challenges

2.1. Taxonomy of Recommendation Approaches

Recommender systems originated in the early 1990s as information filtering tools designed to assist users in navigating large information spaces [12]. Modern RERS architectures typically comprise four core components: (1) user interaction interfaces, (2) model selection logic, (3) data analysis pipelines, and (4) recommendation generation engines, as illustrated in Figure 1. Users provide explicit queries or implicit feedback, triggering the system to select an appropriate model for filtering and analysis. The recommendation engine processes user and property data to generate ranked lists of properties, leveraging feedback to continuously refine personalization, discover relevant content, and improve recommendation accuracy.

The functional flow shown in Figure 1 represents the architectural adaptation required for the RE domain, which diverges significantly from traditional e-commerce recommendation. Unlike high-frequency consumer goods, RERSs must manage high-stakes, low-frequency transactions where the filtering approach must account for spatio-temporal dependencies, such as geographical proximity to urban infrastructure and neighborhood price volatility. As evidenced in our 59-paper corpus, the User Data block shown in Figure 1 extends beyond simple ratings to include "vague" or "fuzzy" buyer preferences and risk attitudes, necessitating the use of hybrid and fuzzy logic models to handle decision-making uncertainty. In addition, the recommender models highlighted in Figure 1 are configured for the multimodal nature of property data. The DL-based block is important for processing unstructured inputs such as textual attribute information and property imagery, and these are critical for accurate house price prediction and personalized ranking. The "technology adoption gap" is addressed by providing explainable and fair outputs that comply with emerging regulatory standards, through integrating KB filtering and multicriteria decision-making.

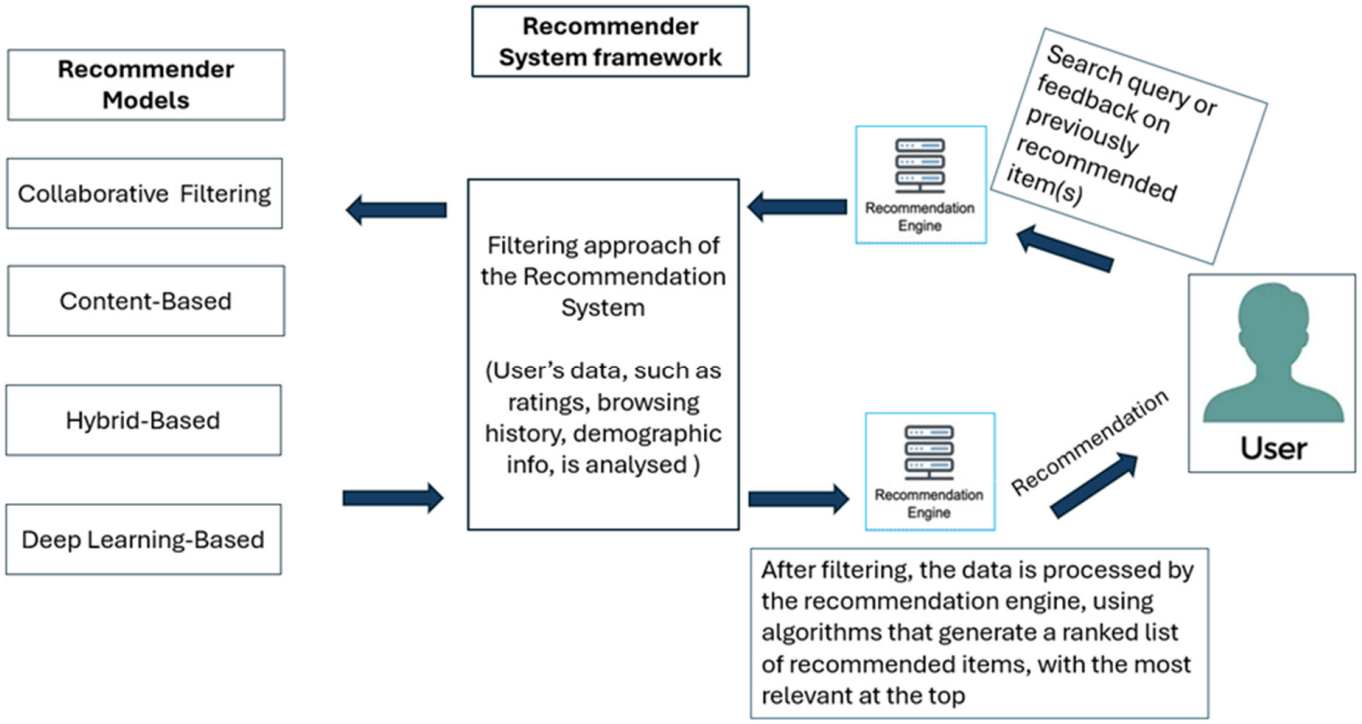


Figure 1. Modern recommender system framework.

RERSs are categorized into four primary types, as shown in Figure 2.

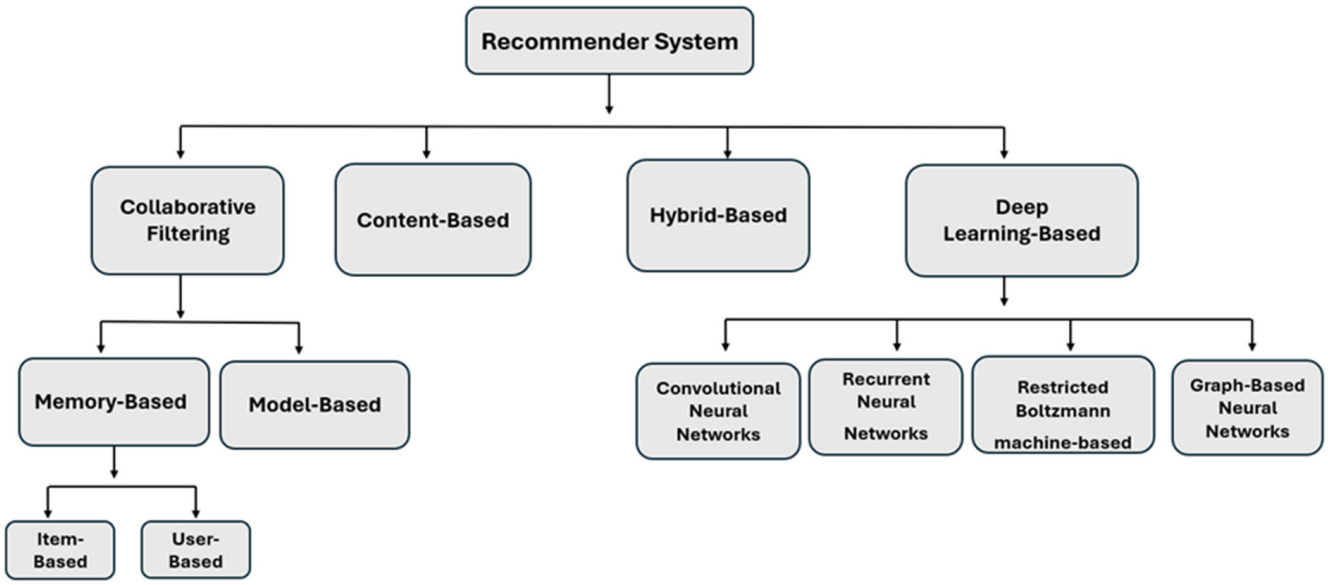


Figure 2. Main types of recommender systems.

Collaborative filtering: CF predicts user preferences based on similarities among users or items, assuming that past agreements will persist over time [13]. Memory-based CF uses neighborhood-based algorithms to estimate preferences from user–item interactions, whereas model-based CF applies predictive methods such as clustering, rule-based models, and Bayesian networks [14]. *Limitation*: CF suffers from severe data sparsity in RE due to infrequent user interactions and long decision cycles.

Content-based: CB methods recommend items similar to those previously preferred by a user, based on attributes such as property size, price, and location [15]. These systems employ content analyzers to extract item features, profile learners to model user preferences,

and filtering components to recommend similar items [16]. *Limitation*: CB systems risk over-specialization and struggle with cold-start users lacking interaction histories.

Hybrid-based (HB): Hybrid systems integrate CF and CB approaches to exploit their complementary strengths [17]. Hybrid models often incorporate ensemble and boosting techniques to improve recommendation diversity and robustness, particularly in high-stakes domains such as housing. *Advantage*: Enhanced accuracy and robustness through method integration.

Deep learning-based systems: DL approaches employ neural architectures such as CNNs, long short-term memory (LSTM) networks, and GNNs to model complex nonlinear relationships in RE data [18]. CNNs extract visual features from property images, LSTMs capture temporal user behavior patterns, and GNNs model spatial and relational dependencies. A hierarchical DL-based personalized housing recommendation architecture has been proposed to improve recommendation efficiency and accuracy [9]. *Advantage*: Ability to handle multimodal data and hierarchical feature representations. *Limitation*: High data requirements and limited interpretability due to opaque model behavior.

2.2. Core Challenges in RERS

Our analysis identifies eight persistent challenges in RERS research, with cold-start and data sparsity dominating the literature. To minimize bias, the classification of research methodologies was subjected to inter-rater verification, achieving a high degree of consensus (Cohen's kappa > 0.75) before final percentage calculations were performed.

1. *Cold-Start Problem* (12/59 studies, 20%): The inability to generate recommendations for new users or new properties due to the absence of historical interaction data [6,19–21]. Strategies such as user profiling, TL, active learning (AL), reinforcement learning (RL), and generative AI have been proposed to mitigate this challenge [21];
2. *Data Scarcity* (9/59 studies, 15%): Insufficient training data due to limited user–property interactions relative to inventory size. Traditional solutions include user-criteria matrices [22] and domain knowledge injection [4];
3. *Interpretability Gap* (0/59 studies implement post hoc XAI): Users demand transparent explanations for high-stakes property decisions; however, complex models such as deep neural networks and ensemble methods operate as black boxes. Although XAI techniques such as SHAP, LIME, and attention mechanisms exist, they remain largely undeployed in RERS;
4. *Algorithmic Bias*: Location-based and historical data-driven recommendations risk perpetuating discriminatory patterns such as redlining. Despite regulatory frameworks (e.g., US Fair Housing Act, GDPR, POPIA), systematic fairness auditing remains rare;
5. *Multimodal Integration*: Effective RERSs must integrate heterogeneous data modalities, including structured attributes, textual descriptions, images, geospatial coordinates, and temporal trends. However, only 3/59 studies (5%) employ multimodal fusion techniques;
6. *Spatio-Temporal Dynamics*: Property markets exhibit strong spatial dependencies (neighborhood effects) and temporal evolution (market cycles). Nevertheless, only 4/59 studies (7%) explicitly model spatio-temporal dynamics;
7. *Evaluation Realism Gap*: Offline evaluation metrics such as Precision@K and NDCG dominate, yet they poorly predict real-world engagement due to preference drift and contextual factors [23];

8. *Scalability*: Real-time recommendation at scale requires efficient architectures for millions of users and properties; however, deployment and system-level performance considerations are rarely reported.

2.3. Why Explainable AI and Transfer Learning Matter

Explainable AI: XAI is the implementation of specific modules (e.g., attention maps, SHAP) that generate human-readable evidence for a recommendation. An XAI-enabled evaluation model does not provide a price only but provides a feature importance plot. In high-stakes domains such as RE, users require transparent and accountable decision logic to trust recommendations. The classification of housing-related AI as "high-risk" under the EU AI Act (Regulation 2024/1689) mandates a shift toward XAI and rigorous bias mitigation in RERS design [24]. XAI techniques provide (1) local interpretability—explaining why a specific property was recommended (e.g., SHAP values identifying proximity to schools as a key factor), (2) global interpretability—understanding general model behavior (e.g., price threshold effects via partial dependence plots), and (3) counterfactual explanations—identifying minimal changes that would alter recommendations. While our corpus shows a 0% adoption of formal post hoc XAI modules, several studies, such as [2], move "toward" local interpretability by visualizing feature importance in DL layers to justify property matching.

Transfer Learning: TL is an ML paradigm where a model developed for a source task is reused as a starting point for a model on a different but related target task. This might involve the systematic reuse of pretrained model weights derived either from a non-RE source (e.g., general object recognition in ImageNet) or a different RE domain (e.g., transferring a model trained from commercial RE to residential RE). RERSs suffer chronic data scarcity, particularly in niche markets (e.g., luxury housing or emerging neighborhoods). TL addresses this challenge through (1) cross-domain transfer—adapting models pretrained on data-rich domains (e-commerce, movies) to RE, (2) cross-market transfer—leveraging knowledge from high-activity markets (e.g., Sandton, South Africa) to low-activity markets (e.g., rural areas), and (3) multimodal transfer—fine-tuning pretrained vision models (e.g., ResNet, VGG) for property image analysis. This is the most active "near-TL" area in our corpus. For instance, refs. [8,9] utilize fine-tuned pretrained vision models to analyze property esthetics, demonstrating the feasibility of feature-based transfer in RE. The near-zero adoption of these mature technologies (XAI, TL) represents one of the most critical research gaps in contemporary RERS. The novelty of this review lies in the proposal of a nine-layer framework. Unlike existing RERS attempts that focus solely on accuracy, e.g., [6], our framework provides a blueprint for transitioning from "black box" models to responsible AI architectures that are explainable, scalable via transfer, and regulation-aware.

3. Methodology

This systematic review adheres to PRISMA 2020 guidelines to ensure transparency, rigor, and reproducibility [25]. The completed PRISMA checklist is provided in Supplementary Materials.

3.1. Search Strategy

We searched the Scopus and Web of Science databases using the query: ("real estate" OR "housing" OR "property" OR "accommodation") AND ("recommender systems" OR "recommendation systems"). The search was restricted to 2005–2025 to focus on modern AI-driven approaches, with pre-2005 seminal works included where relevant. The initial

search was done in May 2025, and a later one in November 2025. The initial search yielded 2240 articles from Scopus and 166 articles from Web of Science.

3.2. Inclusion and Exclusion Criteria

Inclusion criteria: Publication date between 2005 and 2025, peer-reviewed journals and full conference papers, articles written in English, and primary focus on the design, implementation, or evaluation of RERS. Additionally, one thesis [26] was included due to its unique and detailed focus on group recommendation dynamics. *Exclusion criteria*: Non-English publications, unrelated domains (e.g., stock markets, movie recommendation systems), and retracted publications. The initial search yielded 2406 articles, with 14 duplicates removed, resulting in 2392 screened records. The high initial yield was due to the broad inclusion of terms like "property" and "housing", which often appear in unrelated civil engineering or urban planning contexts. The initial pool of 2406 is made up of 2240 from Scopus and 166 from Web of Science. Stage 1 involved removing duplicates (14). Stage 2 involved exclusion based on date range, subject area, document type, publication stage, keywords, language, and Web of Science categories, title and abstract screening. We excluded articles that lacked the technical algorithmic detail or focused solely on traditional economics without a "recommendation" component. After applying inclusion and exclusion criteria, 59 peer-reviewed articles were retained for systematic analysis. The final 59 studies represent the technical intersection of AI-driven recommendation and RE.

3.3. Screening Process

Titles and abstracts were independently screened using the defined selection criteria. Disagreements were resolved through discussion, and a final consensus set of 59 studies was selected. The screening or study selection process is illustrated in the PRISMA flowchart shown in Figure 3, showing that 2406 records were retrieved, 14 duplicates removed, 2392 records screened, and 59 articles included.

3.4. Data Extraction

It should be acknowledged that achieving comprehensive coverage of all published studies on RERS between 2005 and 2025 is inherently challenging, if not unattainable. While this limitation may introduce certain constraints on the interpretation of specific trends identified, the selected 59 representative studies capture the principal technological developments in the field. Each paper was coded according to publication year, addressed challenges, RS paradigm, datasets, RE type, geographic location, document type, AI techniques, and system deployment characteristics, enabling systematic trend analysis.

3.5. Coding Framework and Quality Assessment

To ensure methodological rigor and reproducibility, a structured coding framework was developed to systematically classify and evaluate the selected studies. Each of the 59 included articles was independently coded across multiple dimensions to capture technological, methodological, and contextual characteristics of RERS.

3.5.1. Coding Dimensions

The coding framework comprised eight primary categories:

1. *Recommendation Paradigm*: Studies were classified as CF, CB, hybrid, DL-based, or other emerging paradigms;
2. *Data Modalities*: We recorded whether studies used structured property attributes, user interaction logs, textual descriptions, images, geospatial data, temporal data, or multimodal fusion of multiple modalities;

3. *AI and Machine Learning Techniques*: Algorithms were categorized into traditional machine learning (e.g., k-nearest neighbors, matrix factorization, decision trees), DL (e.g., CNNs, LSTMs, GNNs, transformers), and ensemble methods;
4. *XAI*: Studies were coded for the presence of post hoc or intrinsic interpretability mechanisms, including SHAP, LIME, attention-based explanations, rule extraction, or counterfactual explanations;
5. *TL*: We recorded whether pretrained models, domain adaptation, cross-market transfer, or multimodal pretrained architectures were employed;
6. *Spatio-Temporal Modeling*: Studies were coded based on whether they explicitly modeled spatial dependencies (e.g., neighborhood graphs, geospatial kernels) and temporal dynamics (e.g., time-series forecasting, sequential recommendation);
7. *Evaluation Protocols*: Evaluation methods were classified as offline (e.g., Precision@K, Recall@K, NDCG), online (A/B testing, user studies), or simulation-based;
8. *Ethical and Fairness Considerations*: We identified whether studies addressed fairness, bias mitigation, regulatory compliance, or responsible AI considerations.

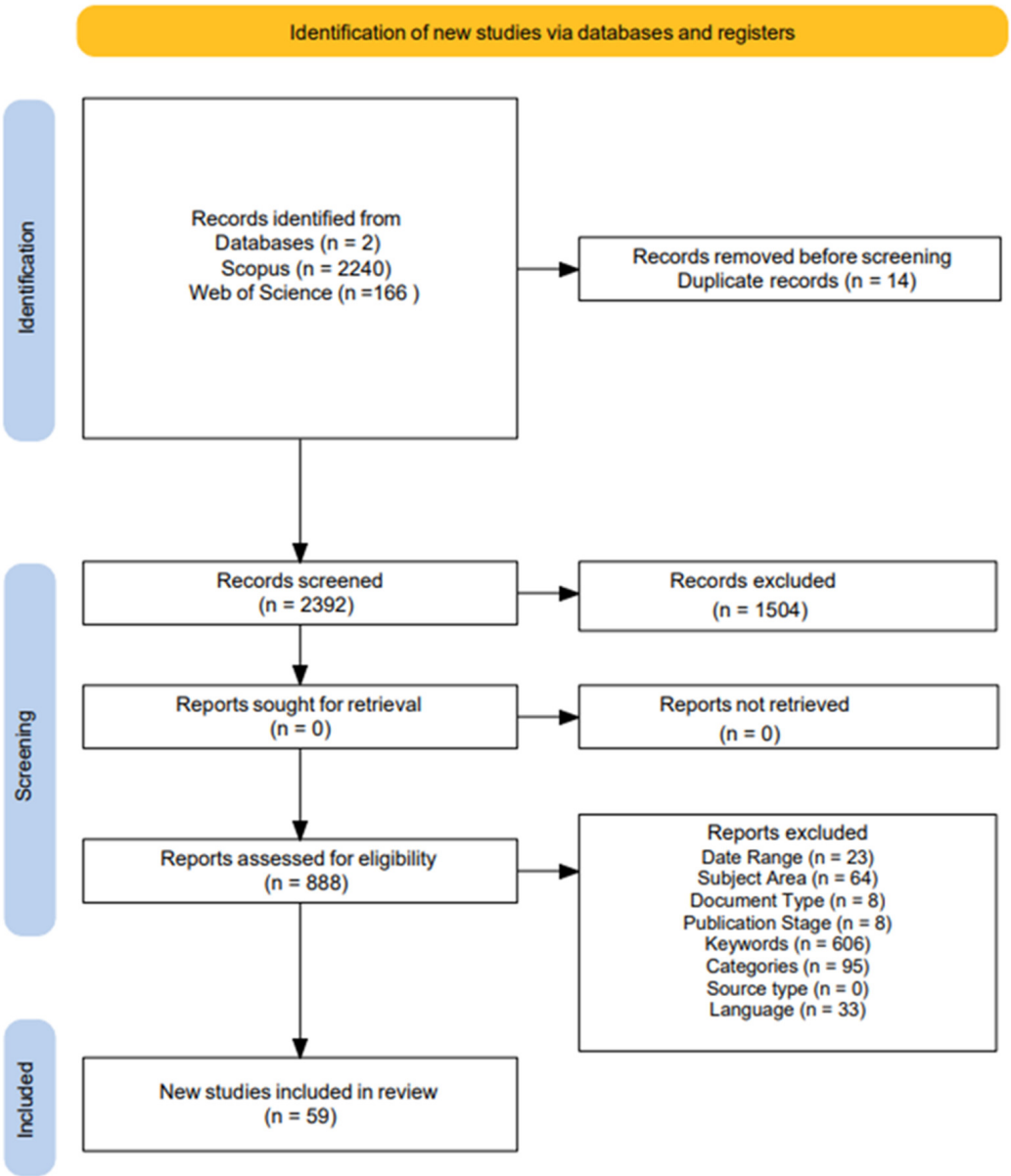


Figure 3. PRISMA 2020 flow diagram for the review methodology.

3.5.2. Coding Procedure and Reliability

Each paper was coded manually using a structured extraction template. To ensure consistency, an iterative coding process was employed, where initial codes were refined through pilot testing on a subset of studies before full-scale coding. To enhance reliability, coding criteria were defined explicitly for each category (e.g., a study was considered XAI-enabled only if it implemented a recognized explainability technique rather than merely discussing interpretability conceptually). This conservative coding strategy ensures that reported adoption rates represent actual methodological implementation rather than conceptual discussion.

To assess coding reliability, a subset of the reviewed studies was independently coded by the two authors using the predefined coding framework. Inter-rater agreement was evaluated using Cohen's kappa coefficient (κ). The coding achieved substantial agreement ($\kappa > 0.75$), indicating high consistency across coding dimensions. Discrepancies were resolved through discussion and consensus adjudication to ensure consistent classification across all included studies.

4. Discussion Results: Descriptive and Thematic Analysis

4.1. Publication Trends and Geographic Bias

4.1.1. Publication Trends

Figure 4 illustrates the temporal evolution of research on RERS from 2005 to 2025. Publications remained sparse until approximately 2014, followed by a sharp increase after 2015. The marked increase in RERS-related publications from 2020 onward coincides with the broader transition toward DL architectures and the rapid digital transformation of the property market during the COVID-19 pandemic. While our data shows a temporal correlation between these events and heightened research output, the surge likely reflects a confluence of these factors.

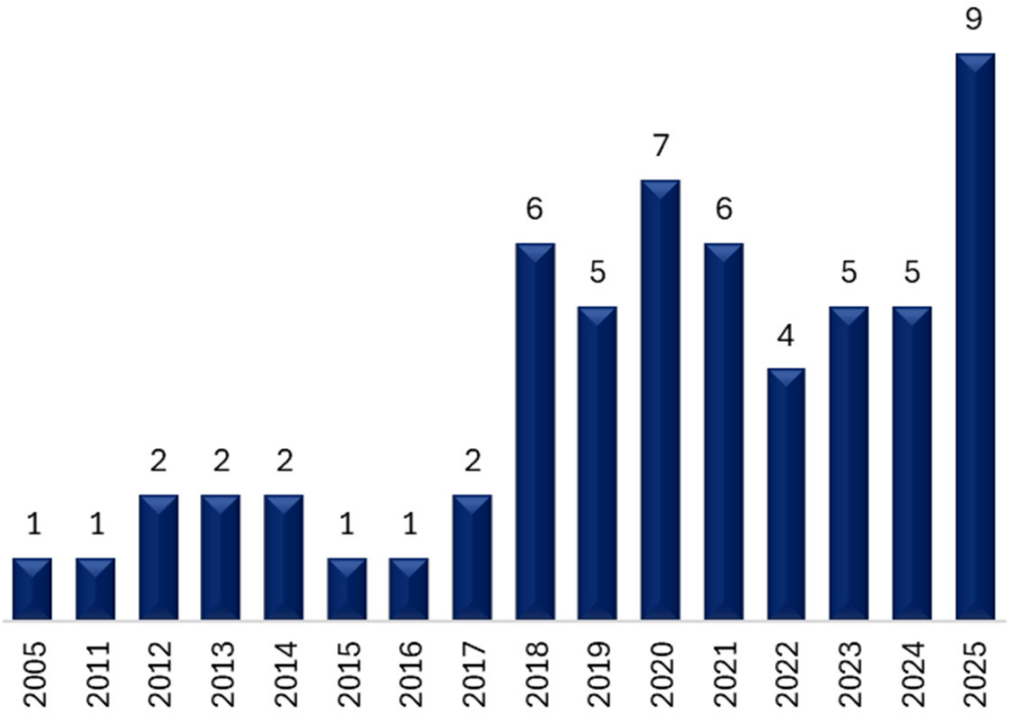


Figure 4. Distribution of publishing year and progression in the number of articles.

Early work focused on multicriteria decision analysis and preference modeling, with studies integrating spatial decision frameworks and user preference modeling [27–29].

Between 2014 and 2016, research shifted toward personalized and risk-aware recommendation frameworks, probabilistic relational models, and case-based reasoning approaches, reflecting growing interest in real-time personalized decision support [10,30–32].

From 2017 to 2019, hybrid recommender systems combining CF, CB, and knowledge-based (KB) approaches became prominent, alongside the integration of geographical proximity as a contextual factor [5,33,34]. During this period, early DL models, including neural tensor networks and context-aware architectures, were introduced to enhance recommendation accuracy and personalization [35,36].

The period from 2020 onward marks the transition toward advanced AI-driven RERS. Generative adversarial networks, embedding-based representations, spatio-temporal–semantic models, and multimodal frameworks were proposed to handle complex and high-dimensional data [2,37–40]. Subsequent studies examined various DL architectures and ensemble ML methods, including CNNs, LSTMs, random forests, decision trees, and XGBoost, for property recommendation and price prediction [41–43].

Recent studies (2024–2025) explored fuzzy logic-based recommendation models, hierarchical architectures, and hybrid location-aware recommender systems, highlighting the increasing complexity and domain specificity of modern RERS [3,9,44,45]. Contemporary research also reflects a growing interest in multimodal data fusion, spatial modeling, and personalized DL-driven frameworks for RE decision support.

Systematic reviews published in 2021 and 2025 confirm the accelerating research activity and identify CF, CB, KB, and hybrid approaches as dominant paradigms, with DL methods such as CNNs and LSTMs emerging as promising but underutilized techniques [6,8]. However, these reviews report limited adoption of advanced AI paradigms, including multimodal learning, spatio-temporal modeling, explainable AI, and TL, underscoring a persistent methodological gap in the field.

4.1.2. Document Type and Publication Venues

Journal and conference publications each account for approximately 49% of the reviewed studies (Figure 5), indicating balanced dissemination across archival and fast-paced research venues. High-impact journals such as *Applied Sciences*, *Expert Systems with Applications*, *European Journal of Operational Research*, and *Decision Support Systems*, along with leading conferences (e.g., ACM-affiliated venues), dominate the publication landscape. The interdisciplinary nature of RERS research, spanning computer science, urban studies, and data science, has contributed to the steady increase in scholarly output and the rising academic visibility of the domain.

4.1.3. Geographic Bias

Datasets used in RERS research exhibit pronounced geographic imbalance. Of the 39 datasets reviewed, 56% originate from Asia (22 datasets), 23% from Europe (9 datasets), 12.8% from North America (5 datasets), and only 2.6% each from Africa, Oceania, and South America (1 dataset each), as shown in Figure 6. The datasets comprise 32 local private listing platforms, 5 public datasets, and 2 Kaggle datasets, highlighting the dominance of proprietary data sources in the field.

The prevalence of Asian datasets can be attributed to several interrelated factors. Asia accounts for approximately 60% of the global population and is undergoing rapid urbanization and digital transformation, resulting in increased RE activity and the widespread adoption of online property platforms. The concentration of research institutions and data science communities in Asia further contributes to higher data collection and publication volumes. Moreover, the growing adoption of data-driven decision-making in Asian RE

markets has intensified research interest in predictive modeling and recommender systems, thereby expanding dataset availability.

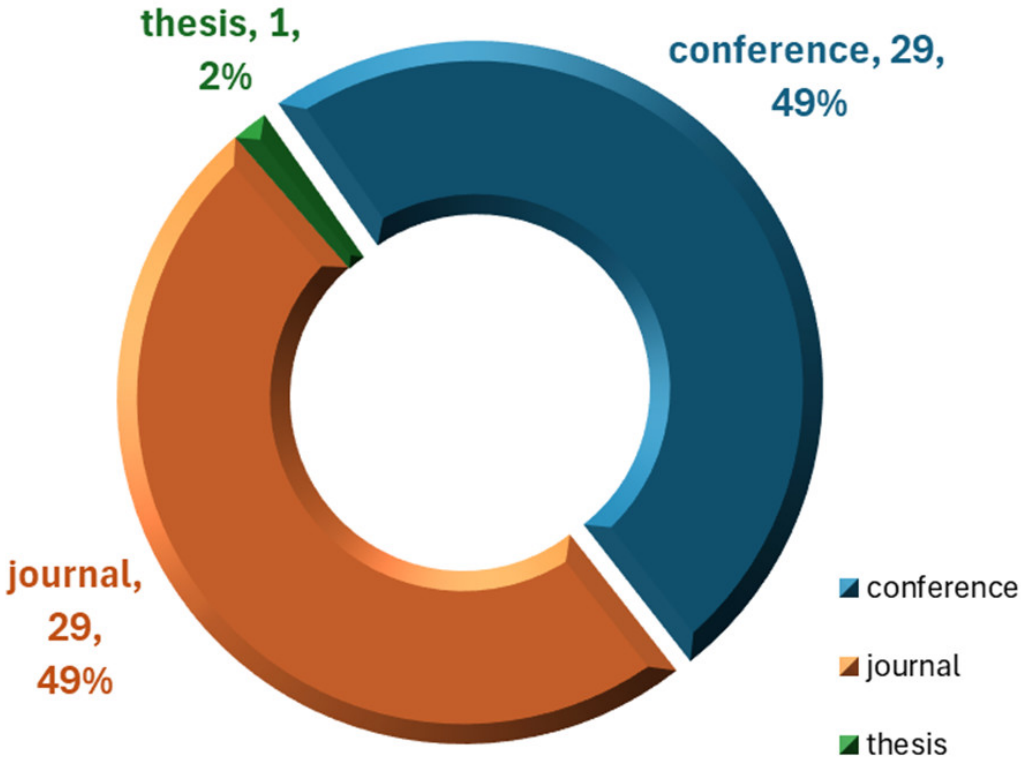


Figure 5. Publication venues.

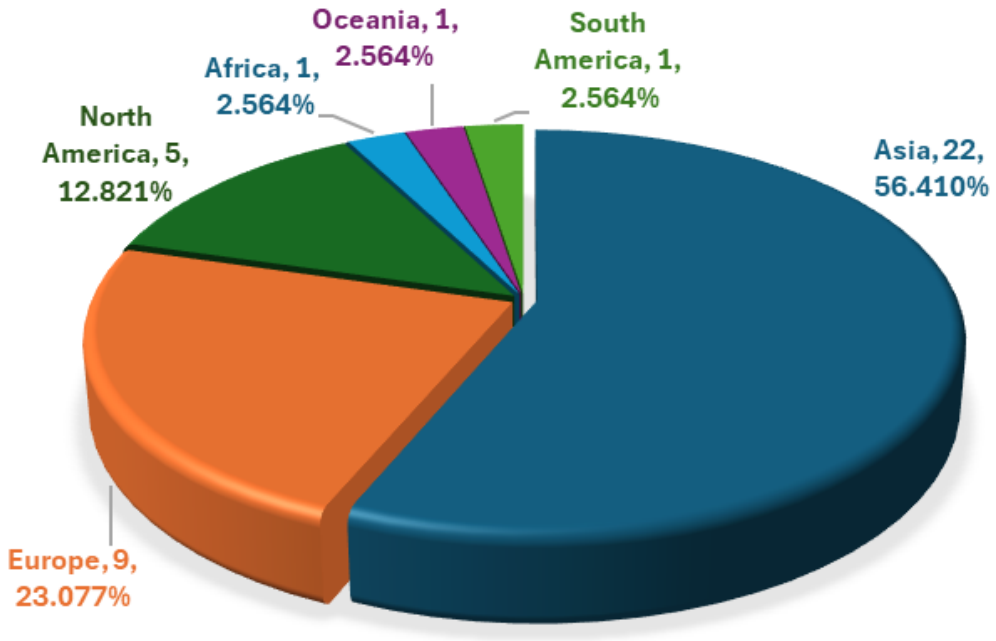


Figure 6. Geographical locations.

Feature diversity also varies substantially across regions due to differences in market characteristics, data accessibility, and research priorities. Asian datasets typically include a broader range of interior and exterior attributes, reflecting detailed listing practices and research emphasis on fine-grained property evaluation. North American datasets often prioritize location-specific and amenity-related features, consistent with market

preferences where proximity to recreational facilities and lifestyle amenities significantly influences property valuation. The absence of reported attributes for Europe's industrial dataset and Asia's commercial dataset likely reflects proprietary constraints, limited dataset availability, or the relatively small number of studies focusing on non-residential property segments. Industrial and commercial RE datasets are inherently heterogeneous, with specialized attributes that are less standardized and more difficult to capture, leading to sparse reporting in the literature.

The near-complete absence of African RE contexts in our systematic review, where one study was identified from the African continent among 59 reviewed, reflects broader patterns of algorithmic inequality. Building on the work of [46], the RERS landscape faces challenges related to structural data-asymmetric sovereignty, sometimes referred to as "data-imperialism". This involves the exportation of algorithmic standards and data harvesting norms from dominant markets to emerging ones. In the RE context, this manifests when recommendation engines optimized for high transparency markets are applied to regions with different land-tenure systems. This gap is particularly consequential given that African property markets are experiencing rapid digitalization.

African RE markets differ in several critical ways that current RERSs fail to address. First, informal property rights and customary tenure systems, which govern approximately 90% of land in sub-Saharan Africa, are not captured in conventional property datasets [47]. Second, rapidly evolving urban morphologies driven by informal settlements create dynamic spatial patterns that violate the stationarity assumptions of most recommendation algorithms. Third, diverse cultural preferences for property features, such as extended family compounds, community spaces, and climate-appropriate designs, require different feature engineering approaches than Western models. Fourth, unique affordability constraints and financing mechanisms (including group savings schemes and informal credit) necessitate fundamentally different recommendation strategies than those optimized for Western mortgage markets.

4.1.4. Property Type Bias

Residential RE overwhelmingly dominates RERS research, accounting for 91% of the reviewed studies, while commercial and industrial properties represent 6% and 3%, respectively, with no studies addressing agricultural or special-purpose properties (Figure 7). Commonly reported residential attributes include location, price, and the number of bedrooms, with regional variations in feature emphasis: Asian datasets frequently include detailed interior and exterior characteristics (e.g., heating systems and landscaping), whereas North American datasets often incorporate amenity-related attributes such as proximity to golf courses. Asia contributes the largest number of residential datasets (16), followed by North America (2 residential and 1 commercial) and Europe (3 residential, 1 industrial, and 1 commercial), with Africa, Oceania, and South America each contributing a single residential dataset.

Several factors explain the dominance of residential property research. First, residential datasets have lower barriers to entry, as housing data are more widely available and less proprietary compared to commercial or industrial RE data, which often require specialized domain knowledge and restricted access [48]. Second, the stable and large-scale demand for housing driven by population growth and urbanization makes residential RE a central research focus. Third, residential RE has substantial economic significance, influencing household wealth, investment decisions, and macroeconomic stability. Fourth, government policies such as zoning regulations, subsidies, and tax incentives disproportionately affect housing markets, motivating research on residential property dynamics. Finally, housing

has critical social implications, including affordability, accessibility, and inequality, which further drive scholarly attention.

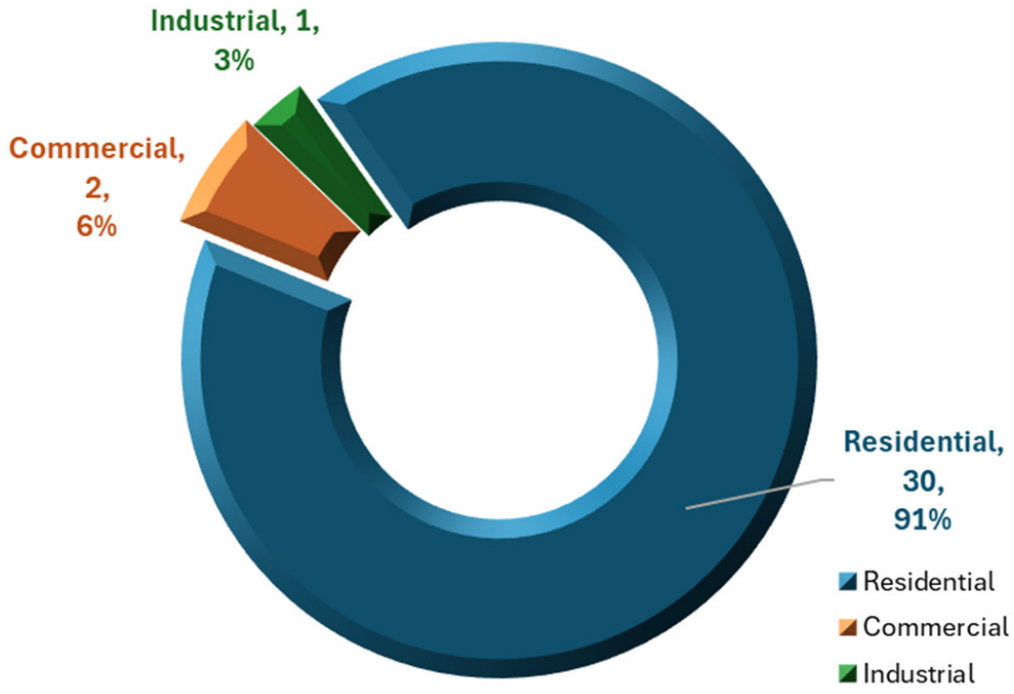


Figure 7. Distribution of real estate type.

In contrast, commercial, industrial, agricultural, and special-purpose RE sectors remain underrepresented due to limited data availability, higher complexity, and the need for specialized knowledge. These property categories exhibit heterogeneous and non-standardized features that are difficult to model, contributing to sparse reporting and limited methodological development in the literature [49]. This concentration on residential datasets limits the external validity of existing RERS models and highlights the need for cross-sector RE recommender frameworks that address commercial, industrial, and agricultural markets.

4.2. Algorithms and Architectures

RERSs employ a diverse range of algorithmic paradigms, evolving from traditional heuristic-based methods to advanced DL architectures. CB systems leverage property attributes such as price and size [15], while CF predicts user preferences based on similar users' behaviors [13]. Hybrid approaches integrate CB and CF to improve robustness. More recently, DL architectures, including CNN-LSTM pipelines for multimodal image-sequence modeling and GNNs for spatial relational learning, have been proposed [50]. Reinforcement learning (RL) is emerging for sequential decision-making in dynamic recommendation environments [51]. However, a critical gap persists in the adoption of transformer-based architectures for spatial-temporal attention modeling, which has been overlooked in prior reviews [8], despite demonstrated potential in recommender systems [52].

4.2.1. Traditional Methods

The reviewed studies were classified into eight methodological categories: CF, CB, HB, multicriteria decision-making (MCDM), knowledge-based (KB), RL, session-based (SB), and item-based (IB), as summarized in Figure 8. CF remains the most prevalent approach, discussed in 25 studies (36%), followed by CB (16 studies, 23%), HB (10 studies,

14%), MCDM (8 studies, 11%), KB (6 studies, 9%), RL and SB (2 studies each, 3%), and IB (1 study, 1%).

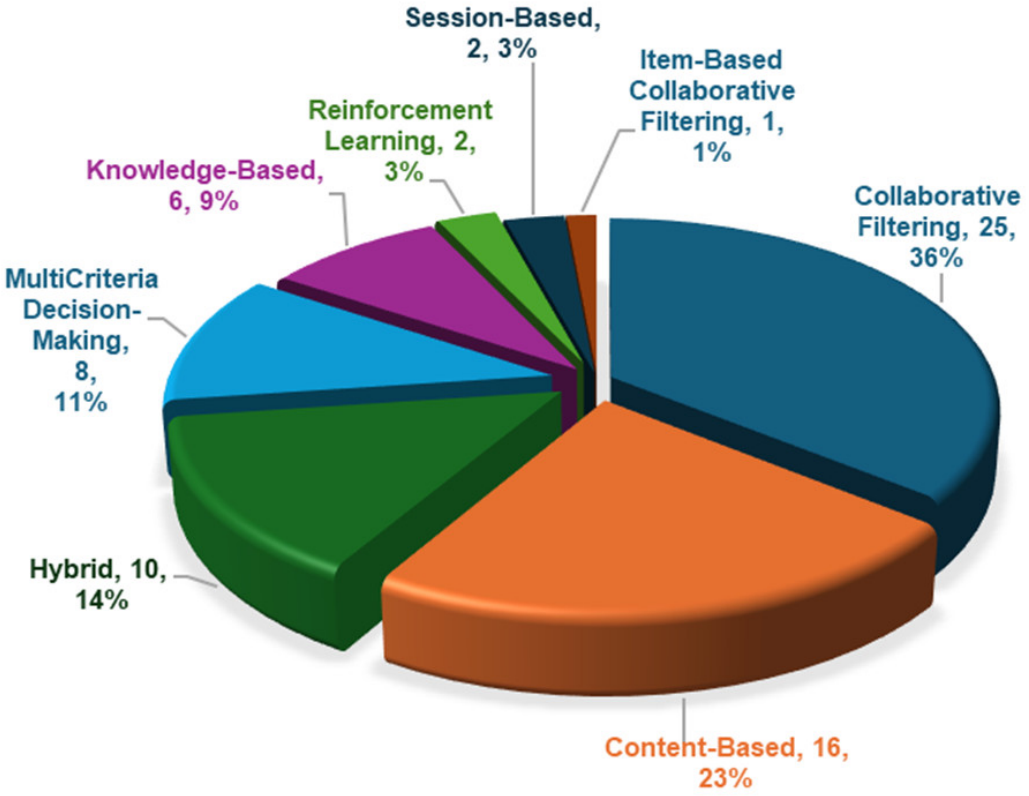


Figure 8. Distribution of recommender system types.

Content-Based Approaches

CB recommendation methods rely on property attributes such as location, price, and size. For example, a two-stage CB recommendation system using Australian datasets selected top users per property using one-hot encoded features and XGBoost-based interaction probability estimation [21]. Cold-start mitigation using CB, KB, and SB approaches was explored using Thai RE datasets [20]. Neural tensor networks and word2vec embeddings were also employed to model property similarity and infer user preferences [35], while cosine similarity-based CB systems provided ranked property lists for user sessions [53].

Collaborative Filtering Approaches

CF is widely used in RERS and across other recommender system domains. Several studies utilized CF for property recommendation and price prediction, including implementations using Turi Create, Keras regression, and linear regression [2]. Neural network-based CF models learned embeddings from user–item ratings [2], while geographic proximity-enhanced CF models exploited spatial correlations [34].

Embedding-based models, such as SeoulHouse2Vec, predicted user–item ratings using neural CF [54]. kNN-based CF achieved high predictive accuracy compared to logistic regression on Kaggle datasets [55]. Hybrid CF-based RERS frameworks, such as RE-RecSys, integrated CB, rule-based, and CF approaches [56]. Other studies employed TF-IDF-based textual modeling [57], recurrent architectures [36], and factorization machine comparisons [58]. Despite their prevalence, CF-based methods suffer from data sparsity and cold-start challenges, which remain insufficiently addressed using modern TL strategies [6].

Hybrid Approaches

Hybrid recommender systems integrate CB and CF to mitigate individual method limitations. Examples include fuzzy rule-based hybrid systems [59], WRMF- and IKNN-based hybrid architectures [17], and location-based hybrid systems integrating CB and CF [45]. Hybrid models are increasingly adopted to improve recommendation accuracy and diversity, particularly in property search and marketing applications [60].

Knowledge-Based and Multicriteria Systems

KB systems employ ontologies and expert knowledge to model relationships among property attributes and user preferences [29]. Decision-support frameworks such as the analytic hierarchy process [28] and case-based reasoning [30] have been applied to housing recommendation tasks. Multicriteria decision-making approaches, including Pareto optimization [27], fuzzy goal programming [31], and PROMETHEE II ranking [40], enable users to evaluate trade-offs among price, location, travel time, and property characteristics.

Context-Aware Recommender Systems

Context-aware recommender systems (CARS) incorporate contextual signals such as time, location, and user activity to generate dynamic recommendations. A DL-based CARS framework employed a Gated Orthogonal Recurrent Unit for candidate generation and contextual ranking, enabling real-time personalized property recommendations [36]. These approaches demonstrate improved alignment with user intent compared to static historical models.

4.2.2. Advanced Methods

Machine learning (ML) and DL techniques were used in 32 reviewed studies, with 72% using ML and 28% using DL, as illustrated in Figure 9. ML models such as XGBoost, kNN, logistic regression, artificial neural networks, clustering methods, and matrix factorization remain dominant due to their interpretability and suitability for limited datasets [34,39,55].

DL architectures, including CNN-LSTM pipelines for multimodal property data [9,18] and GNNs for modeling user–property–location graphs [50], provide enhanced representation learning capabilities. Regression-based models were used in six studies [2,20,55,61–63], clustering methods in two studies [7,26], and ANN/CNN-based approaches in two studies [39,41]. Large-scale distributed ML frameworks using Hadoop and Spark were also reported [32]. Despite these advances, several critical methodological gaps remain:

1. *Graph-Based Recommender Systems*: GNNs offer the ability to capture spatial and relational dependencies among users, properties, and locations, but remain underexplored in RERS;
2. *Reinforcement Learning*: RL-based frameworks can optimize long-term user engagement through sequential interaction modeling, yet adoption is limited;
3. *NLP and Large Language Models*: NLP and LLMs enable conversational property search, semantic understanding of listings, and extraction of insights from unstructured text, but remain largely conceptual in RERS;
4. *Transfer Learning*: TL is particularly suited for data-scarce RE domains, yet no reviewed study implemented TL-based RERS;
5. *Multimodal Recommendation Systems*: Integrating textual, visual, and geospatial modalities remains rare, despite its potential to enhance recommendation diversity and accuracy.

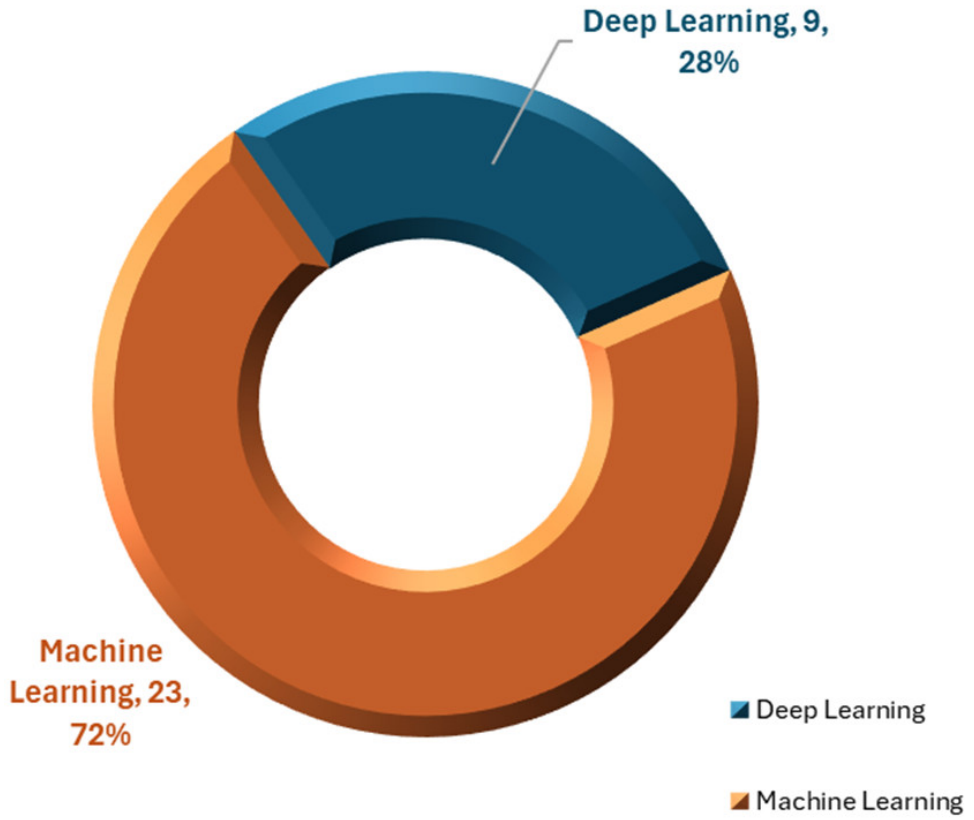


Figure 9. Proportion of AI techniques.

Overall, while traditional ML approaches dominate due to data constraints and interpretability, DL-based models demonstrate a superior representational capacity for complex, multimodal RE data. However, the limited adoption of cutting-edge AI paradigms highlights a significant methodological maturity gap in RERS research. These findings indicate that RERS research remains dominated by traditional CF and CB paradigms, with limited transition toward modern AI architectures such as transformers, GNNs, and LLM-based recommenders. This methodological inertia underscores the need for next-generation RERS frameworks that integrate multimodal learning, TL, and explainability by design.

4.2.3. The Technology Adoption Gap: XAI and TL

A key and unexpected finding of this review is the near-total absence of advanced AI paradigms in RERS, as summarized in Table 2.

Table 2. Advanced techniques analysis.

Technique	Studies Implementing	Percentage
XAI	0/59	0%
TL	0/59	0%
Spatio-Temporal Modeling	4/59	7%
Multimodal Fusion	3/59	5%
Fairness Auditing	2/59	3%

This absence is striking given that XAI and TL have become mainstream in recommender systems, healthcare, finance, and autonomous systems. Their complete omission in RERS highlights a systemic methodological stagnation in the domain. Possible explanations include the following:

First, an *academic–industry disconnect* persists, with researchers prioritizing offline accuracy metrics rather than interpretability, deployability, and regulatory compliance

required in practice. Second, *methodological conservatism* may discourage the adoption of novel approaches, as reviewers and journals often impose higher evidentiary standards for unconventional methodologies. Third, *implementation complexity* limits adoption, as XAI and TL require interdisciplinary expertise spanning computer vision, NLP, RE economics, and human–computer interaction. Finally, *evaluation challenges* persist, as standardized benchmarks for interpretability and transfer effectiveness in RERS are lacking. This gap strongly motivates the need for next-generation RERS frameworks that integrate transparency, domain adaptation, and fairness auditing.

4.3. Challenge Algorithm Mapping

The reviewed studies primarily addressed cold-start, data scarcity, sparsity, scalability, privacy, over-specialization, conflicting criteria, bias, and information overload. As shown in Figure 10, cold-start was the most frequently studied challenge (12 articles), followed by data sparsity (9 articles). Cold-start is particularly dominant because CF relies heavily on historical user–item interaction data, which is unavailable for new users or newly listed properties.

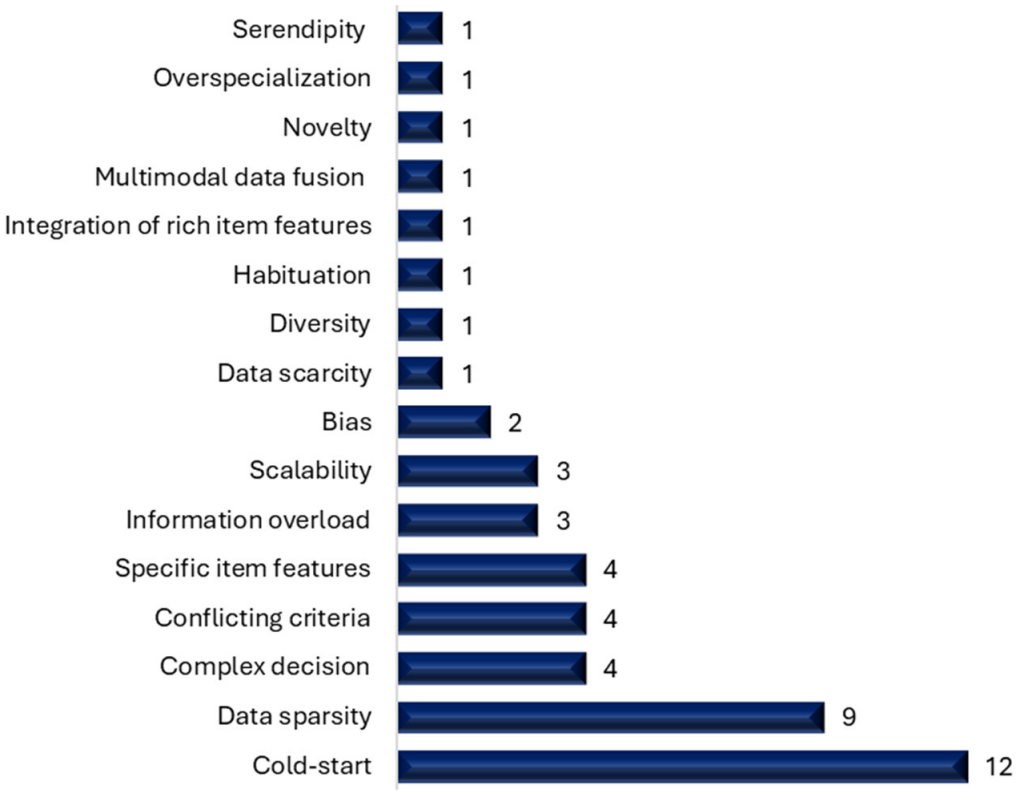


Figure 10. Recommender system challenges.

Common mitigation strategies included user profiling, CB bootstrapping, hybrid models (HBs), and KB approaches. Data sparsity also remains critical in RERS because user interactions with property listings are sparse and uneven, and property inventories change dynamically. Consequently, cold-start and sparsity are prioritized due to their direct impact on recommendation accuracy, system scalability, and user satisfaction. However, most solutions remain incremental, relying on traditional CF and CB frameworks rather than leveraging recent advances in representation learning, TL, and multimodal fusion.

4.4. Data Modalities and Fusion

RERSs increasingly exploit heterogeneous data modalities, including text, images, audio, video, geospatial data, and numerical attributes such as price and property size. Multimodal fusion techniques and cross-modal retrieval methods enhance recommendation accuracy and user experience by integrating complementary information sources.

A dynamic RERS combining text mining and image recognition was proposed to provide timely property information to agents and consumers [41]. RE-RecSys introduced an end-to-end pipeline integrating categorical and numerical property features for different user profiles [56]. Zenden employed CNN-based image classification to recommend properties based on user browsing history [18].

Gap Analysis. Despite these advances, modern multimodal AI systems such as CLIP, DALL-E, and multimodal LLMs (e.g., GPT-4V, Gemini) remain absent in RERS research. Future opportunities include image–text alignment for quality assessment of property listings and generative virtual staging to enhance property visualization and user engagement.

4.5. Spatio-Temporal Modeling

Spatio-temporal modeling integrates geographic and temporal dynamics to produce context-aware property recommendations. RE markets are inherently dynamic, with evolving user preferences, spatial heterogeneity, and temporal price fluctuations. The spatio-temporal framework for RE appraisal integrated recurrent neural networks and heterogeneous graphs to model temporal and spatial dependencies [52]. Location-based recommendation frameworks and regression kriging methods further demonstrated improved predictive accuracy [2,63]. The spatial–temporal–semantic model combined spatial, temporal, and semantic information using Gaussian processes and stochastic gradient optimization [38].

Gap Analysis. Only 4 of 59 studies explicitly modeled spatio-temporal dynamics, neglecting critical real-world factors such as school district changes, infrastructure development, and seasonal market fluctuations. This underutilization represents a significant research opportunity.

4.6. Evaluation Practices

Evaluation in RERS traditionally relies on offline metrics such as Precision, Recall, F1-score, and Mean Average Precision. While these metrics quantify predictive accuracy, they fail to capture user satisfaction, trust, and real-world decision utility. Emerging user-centric evaluation metrics address perceived usefulness, satisfaction, and engagement, but their adoption remains limited. Comprehensive evaluation frameworks should integrate offline metrics, online A/B testing, user studies, and fairness assessments to reflect real-world deployment scenarios.

4.7. Explainability and Transparency

Explainability is the degree to which a model's recommendations can be interpreted by people [64,65]. Explainable RERS architectures mitigate the interpretability challenge by generating human-understandable justifications for recommendations. Three dominant paradigms are rule-based explanations [56,66], case-based explanations [30], and model-based explanations using SHAP, LIME, or attention mechanisms [67,68].

Rule-based explanations provide transparent decision logic but lack adaptability. Case-based explanations improve trust by referencing similar users or properties. Model-based explanations offer local and global interpretability but require advanced visualization and user comprehension frameworks. Existing studies highlight the interdisciplinary nature

of explainable recommender systems and the critical need for transparency in high-stakes domains [69–72].

Advanced XAI Techniques

SHAP quantifies feature contributions for tabular data, enabling explanations of property recommendations. Grad-CAM visualizes salient regions in property images, and attention heatmaps highlight influential textual features in descriptions and reviews. These methods provide actionable transparency for stakeholders.

4.8. Other AI Techniques

Beyond CF and CB, advanced AI techniques such as fuzzy logic, deep neural networks, autoencoders, and AL have been applied to RERS [15]. Fuzzy logic models uncertainty in vague user preferences [73]. DNNs capture nonlinear relationships among user, property, and contextual features [74]. Autoencoders support dimensionality reduction and synthetic data generation to mitigate sparsity. AL reduces labeling costs by querying informative user interactions [75]. TL remains a promising but underexplored paradigm, enabling the adaptation of pretrained vision and language models to RE applications, including property image analysis and semantic text understanding.

4.9. Ethical and Fairness Considerations

Ethical RERSs must address privacy, fairness, transparency, and regulatory compliance. Compliance with GDPR, POPIA, and the US Fair Housing Act is essential to mitigate discriminatory outcomes. Location-based recommendations risk redlining and reinforcing socioeconomic inequalities. Proposed fairness metrics include demographic parity, disparate impact, and equal opportunity, supported by auditing tools, user understanding assessments, anonymization effectiveness, and compliance audits. Diversity analysis across demographic groups has been explored in limited studies [56], indicating the infancy of fairness-aware RERS research.

5. Critical Appraisal: Gaps, Limitations, and Proposed Conceptual Framework

Despite two decades of research, RERSs continue to face systemic bottlenecks that constrain their scientific maturity and real-world deployment. This section critically synthesizes six fundamental limitations and proposes a forward-looking conceptual framework to guide future research.

5.1. Data Bottleneck

Data sparsity, inconsistent quality, and the scarcity of public multimodal datasets remain dominant barriers to RERS development. Among the reviewed studies, only five public datasets were identified, which is insufficient for modern DL requirements. This lack of standardized, large-scale datasets severely limits reproducibility, benchmarking, and methodological innovation.

The absence of unified schema standards for multimodal property data (e.g., price, images, textual descriptions, geospatial attributes) further hampers interoperability and cross-study comparability. Community-driven dataset initiatives, standardized schemas, and collaborative data-sharing platforms are urgently needed to enable robust model training, comparative evaluation, and accelerated progress in RERS research. Addressing this data bottleneck should be a central priority in the future research agenda.

5.2. Methodology Bottleneck

Significant methodological transparency issues were identified, including undocumented preprocessing pipelines, proprietary dataset dependencies, and overfitting risks in

closed commercial datasets (e.g., 99acres.com) [76]. These practices undermine reproducibility and limit the generalizability of reported findings. To improve methodological rigor, we recommend adopting standardized reporting protocols such as the ML reproducibility checklist [77] and promoting registered reports, where research hypotheses and evaluation protocols are pre-registered before data access. This is particularly feasible for RERSs where the complexity of the black box preprocessing pipelines often undermines reproducibility. By preregistering evaluation protocols, researchers can ensure that their findings regarding spatio-temporal accuracy or fairness are not artifacts of selective reporting on favorable market data, thereby strengthening the overall scientific credibility of the PropTech field. Such practices can mitigate selective reporting, reduce publication bias, and strengthen scientific credibility.

5.3. Evaluation Bottleneck

Evaluation practices in RERS are dominated by offline accuracy metrics such as Precision@K, NDCG, and R^2, with minimal adoption of user studies, online A/B testing, or longitudinal evaluations [56,76]. This reliance on offline metrics creates an "accuracy trap", where models are optimized for historical data performance without validating real-world utility. We coded a paper as "offline evaluation" if it reported standard quantitative performance metrics (RMSE, Precision, MAE, etc.). Table 3 highlights the limitations.

Table 3. Evaluation methods in real estate recommender systems.

Evaluation Method	Usage in Studies	Real-World Impact	Key Limitations
Offline (historical data)	20%	Low	Ignores preference drift, context, trust, and fairness; measures only historical accuracy.
Online (A/B testing)	0%	High	Expensive, slow, requires a large user base and infrastructure.
User studies	2%	Medium	Small samples, artificial settings; limited ecological validity.
Longitudinal tracking	0%	Highest	Requires long-term commitment, live product integration; rarely feasible in academic research.

5.4. Integrating Trust, Stakeholders, and Fairness

Positioning the T-EVAL within existing RS frameworks While standard RS evaluation often prioritizes algorithmic accuracy (RMSE, Precision, Recall), the high-stakes nature of RE demands a more holistic rubric. T-EVAL is proposed as a synthesis of three established scholarly perspectives: **Trust-based perspective**: Drawing from the ResQue framework [78], T-EVAL evaluates the "Transparency" and "Explainability" of RERS, recognizing that a house is a "credence good" in which user trust outweighs simple click-through rates. **Multi-stakeholder perspective**: Following [79], T-EVAL acknowledges that RERSs operate in a three-sided market (buyers, sellers and platforms). An effective evaluation must account for "provider fairness" (seller visibility) as much as "consumer utility". **Fairness-aware perspective**: Grounded in the taxonomies of [80], T-EVAL incorporates social metrics to identify and mitigate demographic biases in housing recommendations. This ensures compliance with evolving digital housing regulations.

5.4.1. Proposed Solution: Trust-Based Evaluation Framework

We propose the T-EVAL framework (Table 4), which extends traditional accuracy-centric evaluation to include trust, fairness, efficiency, and legal compliance. T-EVAL integrates quantitative metrics with human-centered and regulatory dimensions, addressing the ecological validity gap in RERS evaluation.

Table 4. T-EVAL framework dimensions.

Dimension	Focus	Description
Accuracy	Predictive performance	Precision@K, Recall@K, NDCG, A/B testing; measures preference prediction accuracy.
Trust	User satisfaction and explainability	Likert surveys, Net Promoter Score, explanation quality; evaluates transparency and confidence
Fairness	Equity and bias mitigation	Demographic parity, equalized odds, disparate impact; ensures unbiased recommendations
Efficiency	Business and system impact	CTR, conversion rate, revenue lift; assesses economic and engagement outcomes
Lawfulness	Regulatory compliance	Compliance with fair housing laws, GDPR, POPIA; ensures lawful algorithmic decisions

T-EVAL is a framework for evaluating the performance and impact of algorithmic systems, including RS. It encompasses the dimensions of Accuracy, Trust, Fairness, and Efficiency. We propose a trust-based evaluation framework that incorporates decision confidence (using Likert-scale surveys), user satisfaction (as measured by the Net Promoter Score), and fairness metrics (e.g., demographic parity), along with online protocols (such as A/B testing and longitudinal studies) to address offline bias.

5.4.2. Accuracy-Oriented Evaluation and Predictive Utility

Focuses on measuring the accuracy of the RS's predictions or recommendations. Metrics used are Precision, Recall, F1-score, Mean Absolute Error (MAE), and Mean Squared Error (MSE). Factors that influence predictive utility are data quality, feature engineering, model architectures, and hyperparameter tuning and optimization. The accuracy-oriented evaluation is a fundamental aspect of T-EVAL, as it provides a baseline understanding of the system's performance.

5.4.3. User Trust-Oriented Evaluation

Focuses on measuring the trustworthiness of the RS from the user's perspective. Metrics used are user satisfaction, perceived accuracy, and perceived diversity. Key aspects are transparency, explainability, and interpretability. The goal is to ensure that the system provides transparent, explainable recommendations that align with the user's preferences and values. User trust-oriented evaluation is essential for T-EVAL, as it assesses the system's ability to build and maintain user trust. User-centric metrics include:

- Decision confidence: "How confident is the client in this recommendation?"
- Perceived accuracy: "How well do the recommendations match the client's needs?"
- Explanation quality: "Were reasons for the recommendation clear?"

5.4.4. Fairness- and Bias-Aware Evaluation

Focuses on measuring the fairness and bias of the RS. The metrics used are the disparate impact, disparate treatment, and fairness metrics (e.g., equalized odds, equal opportunity). The goal is to identify and mitigate biases in the system, ensuring that it treats users and items fairly and without discrimination. The fairness- and bias-aware evaluation is a critical aspect of T-EVAL, ensuring the system is fair and unbiased.

5.4.5. Market Efficiency-Oriented Evaluation

The impact of the RS on the market can be measured through market efficiency-oriented evaluation. The metrics used are the click-through rate, conversion rate, and revenue. The goal is to optimize the system's performance in terms of business outcomes, such as increasing sales or engagement. The market efficiency-oriented evaluation

is an important aspect of T-EVAL, as it assesses the system's impact on the business or market.

5.4.6. Lawfulness: Regulatory Compliance

- Fair Housing Act (US): No discrimination by color, race, sex, national origin, religion, family status, or disability;
- GDPR (EU): Right to explanation, data minimization, purpose limitation;
- POPIA (South Africa, Zimbabwe): Consent, data security, transparency.

Offline evaluation alone creates an ecological validity gap, as historical preferences rarely reflect real-time decision-making due to contextual factors, preference drift, and information overload [23]. Metrics such as click-through rate, conversion rate, and dwell time provide more realistic assessments of user engagement. Furthermore, the lack of standardized public benchmarks, unlike MovieLens or Amazon datasets, limits reproducibility and cross-study comparisons. Ethical audits and fairness metrics are essential for socially responsible RERSs.

5.5. Generalization Bottleneck

Geographic bias is pronounced, with 56.4% of datasets focused on Asia, limiting model generalizability to Africa, South America, Europe, and North America. Structural differences in urban density, transportation systems, cultural housing preferences, and land availability reduce feature transferability across regions. Moreover, 91% of studies focus exclusively on residential properties, neglecting commercial, industrial, and agricultural RE. This narrowness domain constrains the applicability of RERS across broader RE sectors.

5.6. Ethical Bottleneck

Minimal fairness audits expose RERS to risks of discriminatory recommendations and digital redlining. Compliance with regulations such as the US Fair Housing Act and data protection laws remains limited. Future RERSs should incorporate counterfactual fairness metrics, bias detection tools, and regulatory compliance mechanisms to ensure equitable and lawful recommendations.

5.7. Deployment Bottleneck

Only one study reported real-world deployment details, highlighting a substantial translational gap between research and practice. Future studies should report deployment architectures, latency benchmarks, scalability tests, cost analyses, and maintenance logs. Standardized deployment reporting guidelines would significantly enhance industrial relevance and reproducibility.

6. Conceptual Framework for Next-Generation RERS

To address the identified challenges, ethical AI practices must be embedded throughout the RERS lifecycle. These include (i) explicit user consent and privacy-preserving data governance, (ii) continuous fairness auditing and bias mitigation, and (iii) transparent recommendation logic that promotes inclusivity, accountability, and user autonomy. Future RERSs must therefore balance predictive accuracy with responsible AI design, ensuring that technological advances such as DL and TL do not compromise trust, fairness, and ethical integrity.

Building on the identified research gaps, we propose a nine-layer conceptual architecture for next-generation RERS that integrates multimodal data processing, spatio-temporal modeling, TL, XAI, and fairness-aware evaluation (Figure 11). The framework aims to

deliver accurate, transparent, and socially responsible recommendations for buyers, renters, investors, and real estate agents.

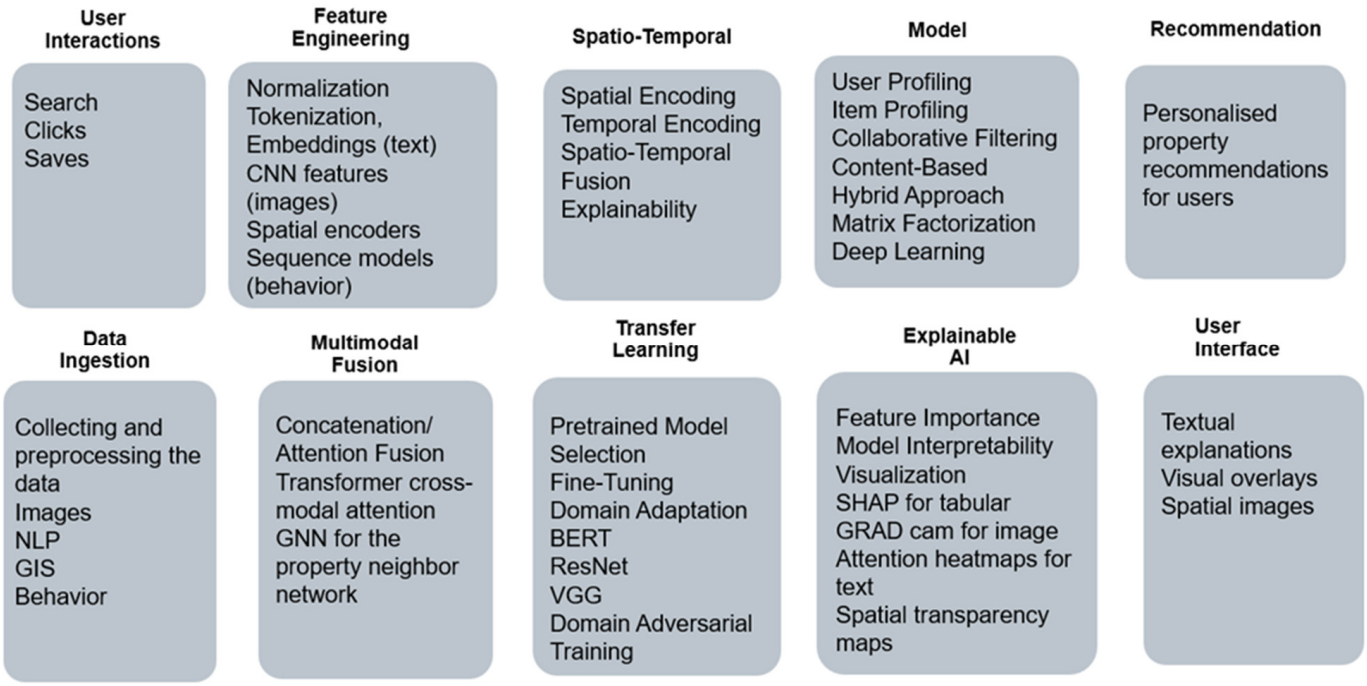


Figure 11. Conceptual framework for the next-generation real estate recommender systems.

Figure 11 presents a nine-layer conceptual framework for next-generation RERS that systematically integrates multimodal data processing, spatio-temporal modeling, TL, XAI, fairness-aware evaluation, and human-centered interaction. Unlike prior RERS architectures that focus primarily on algorithmic recommendation pipelines (e.g., CF, CB, or hybrid models), the proposed framework embeds ethical, regulatory, and trust dimensions as first-class system components. The architecture also explicitly incorporates TL and multimodal fusion to address data scarcity and heterogeneity, while the explainability layer operationalizes transparency and accountability requirements in high-stakes property decision-making. This holistic, socio-technical framework extends beyond predictive performance and positioning.

6.1. Data Ingestion and Preprocessing Layer

This layer consolidates heterogeneous data sources, including structured attributes (price, size, property type), unstructured textual data (descriptions, agent notes, reviews), visual data (interior and exterior images), geospatial information (crime rates, amenities, accessibility), and behavioral logs (clicks, views, inquiries). Robust preprocessing ensures data completeness, normalization, cross-modal synchronization, and noise reduction, which are essential given the heterogeneous, high-dimensional nature of RE data.

6.2. Feature Engineering

This layer transforms raw data into dense, learnable representations that capture latent user and property characteristics. Each modality follows a dedicated transformation pipeline:

- *Tabular data*: numerical normalization, categorical encoding, and feature interactions.
- *Text*: tokenization, contextual embeddings (e.g., BERT), sentiment extraction.
- *Images*: CNN-based feature extraction capturing architectural style, esthetics, and lighting.

- *GIS data*: spatial encoders representing neighborhood topology, accessibility, and urban infrastructure.
- *Behavioral data*: sequential models (LSTM or transformers) capturing evolving user preferences.

6.3. Multimodal Fusion Layer

This layer integrates heterogeneous modalities into unified representations using:

- Concatenation-based fusion;
- Attention-based fusion weighting modality importance dynamically;
- Cross-modal transformers aligning text and image semantics;
- GNNs modeling property–location–user relationships.

Multimodal fusion enables holistic user–property matching, for instance, linking users who prefer "modern kitchens" to visually similar listings even when textual descriptions are incomplete.

6.4. Spatio-Temporal Modeling Layer

This layer captures spatial and temporal dynamics critical to real estate markets, including neighborhood evolution and temporal demand fluctuations. Components include:

- Spatial encoding: graph-based spatial representations and spatial indexing;
- Temporal encoding: time-series models and transformers capturing market dynamics;
- Spatio-temporal fusion: attention-based integration of spatial and temporal signals.

Techniques such as SAR, TAR, STAR, and spatio-temporal GNNs model complex dependencies across space and time.

6.5. Transfer Learning

The TL layer leverages knowledge from data-rich domains to mitigate RE data scarcity through:

- Pretrained language models (e.g., BERT) for textual semantics;
- Pretrained vision models (e.g., ResNet, VGG) for property images;
- Domain adaptation via adversarial training and multi-task learning.

TL accelerates training, improves generalization, and reduces reliance on large, labeled datasets.

6.6. Model Layer

This layer implements recommendation algorithms, including CF, CBF, hybrid models, and DL architectures. Key components include:

- User profiling and item profiling;
- For latent factor discovery, matrix factorization (NMF, SVD) is important;
- GNNs for relational modeling;
- Attention mechanisms for feature importance weighting.

Deep neural architectures enable modeling complex nonlinear relationships in multimodal RE data.

6.7. XAI Layer

The XAI layer ensures transparency and interpretability through:

- Feature importance analysis (e.g., SHAP);
- Visual explanation techniques (Grad-CAM);
- Textual explanation via attention heatmaps;
- Model-agnostic explanation tools (LIME, PDPs);

This layer enables both local and global interpretability, supporting user trust and regulatory compliance.

6.8. Recommendation and Ranking Layer

This layer generates personalized ranked property lists using:

- Learning-to-rank models;
- Deep ranking architectures;
- Hybrid collaborative filtering;
- RL for interactive recommendation.

The objective is to optimize relevance, diversity, and long-term user satisfaction while balancing exploration and exploitation.

6.9. User Interface and Interaction Layer

The interface layer translates model outputs into human-centered explanations, including:

- Textual rationales for recommendations;
- Visual overlays highlighting influential property features;
- Spatial transparency dashboards showing neighborhood characteristics.

This layer closes the human–AI loop, fostering informed decision-making and user trust.

Comparison with Prior RERS Frameworks

Table 5 situates the proposed conceptual framework within the landscape of existing RERS architectures and related recommender system surveys, thereby critically benchmarking its novelty. Prior frameworks have primarily focused on algorithmic pipelines for recommendation generation, emphasizing CF, CB methods, and hybrid learning paradigms with limited integration of advanced AI components [11]. Recent surveys on recommender systems have highlighted emerging challenges such as interpretability, fairness, and multimodal data fusion; however, these dimensions are typically discussed conceptually rather than operationalized within system architectures [69,81].

Table 5. Walkthrough of the nine-layer architecture.

Layer	Component	Functional Instance (Example)	Minimal Metrics/Tools
Data Source	Raw inputs	MLS listings, images	SQL, NoSQL Databases
Feature Extraction	Multimodal processing	Models extract “tiles” or “hardwood floors” from images; NLP extracts “quiet neighborhood” from text	CNNs, BERT, ResNet
Spatio-temporal	Contextualization	Calculates distance to hospital or schools, checks price trends for the past year	GeoPandas
Preference Model	User profiling	Tracks user clicks on modern apartments vs. old apartments to build a latent profile	CF
Candidate Gen	Filtering	Narrows down 1000 listings to 10 possibilities based on location, price and number of bedrooms	Matrix Factorization
Ranking	Scored list	Uses a deep neural network to rank the 10 items by probability of a click	Metric-NDCG
Explainability	XAI layer	Applies SHAP to show, for example, “recommended because of proximity to school”	Tools-SHAP, LIME
Fairness Audit	Bias mitigation	Checks if the model is steering the user away from certain addresses based on demographics	Metric–Demographic Parity
Interface	Delivery	The mobile app UI displaying the house, score, and why it was recommended	Flutter, React Native

In contrast, the proposed framework (Table 6) advances beyond algorithm-centric designs by explicitly embedding multimodal representation learning, spatio-temporal modeling, TL, and XAI as dedicated architectural layers, while also integrating fairness auditing and regulatory compliance mechanisms. This end-to-end socio-technical architecture operationalizes responsible AI principles in the high-stakes RE domain, thereby extending prior RERS frameworks that largely prioritize predictive accuracy and offline evaluation metrics.

Table 6. Comparison of prior RERS and the proposed framework.

Aspect	Prior RERS Frameworks	Proposed Framework (This Study)
Data Representation	Mainly tabular property attributes	Multimodal (text, images, GIS, behavior, temporal)
Learning Paradigm	CF, CB, hybrid ML models	Hybrid ML/DL + GNNs + Transformers
TL	Rarely considered	Explicit TL layer with domain adaptation
Spatio-Temporal Modeling	Limited or absent	Dedicated spatio-temporal modeling layer
Explainability	Ad hoc or rule-based explanations	Dedicated XAI layer (SHAP, Grad-CAM, attention)
Fairness and Ethics	Mostly conceptual	Integrated fairness auditing and regulatory compliance
Evaluation Focus	Offline accuracy metrics	Multi-dimensional T-EVAL (accuracy, trust, fairness, efficiency, lawfulness)
User Interaction	Simple ranking lists	Human-centered explanations and transparency dashboards
System Perspective	Algorithm-centric	End-to-end socio-technical AI system architecture

Notably, prior frameworks typically emphasize recommendation accuracy, whereas this framework operationalizes responsible AI principles for high-stakes RE decision-making. To the best of our knowledge, no prior RERS review has proposed a layered architecture integrating multimodal learning, spatio-temporal modeling, TL, explainability, and fairness evaluation within a unified framework.

7. Conclusions

This systematic review demonstrates that RERS research has reached a pivotal inflection point. Although the field has progressed from traditional CF to DL-based architectures, it has largely failed to adopt transformative techniques such as XAI and TL technologies that are essential for addressing interpretability and data sparsity challenges.

The novelty of this review lies in three contributions:

1. The empirical identification of a technology adoption gap in RERS;
2. The proposal of a next-generation multimodal and ethically grounded conceptual framework;
3. The introduction of the T-EVAL framework, which shifts evaluation beyond accuracy toward trust, fairness, efficiency, and legal compliance.

By highlighting the ecological validity gap between offline evaluation and real-world deployment, this study calls for a paradigm shift toward multimodal, spatio-temporal, and human-centered validation protocols. Future research must prioritize real-world experimentation, fairness auditing, and regulatory-aware system design to ensure responsible and impactful RERS deployment. Ultimately, this review provides the first comprehensive benchmark and research roadmap for transparent, ethical, and intelligent RERS, establishing a foundation for next-generation AI-driven property markets.

8. Policy and Industry Implications

The findings of this review have significant implications for policymakers, RE platforms, and AI practitioners. *Policymakers* must recognize that algorithmic property recommendations can influence housing access, urban segregation, and financial equity. Therefore, regulatory frameworks should mandate transparency, fairness auditing, and

explainability in RERS deployments, similar to requirements emerging in financial and healthcare AI systems.

For *industry*, integrating explainable and fairness-aware RERSs can enhance user trust, regulatory compliance, and market competitiveness. RE platforms that adopt multimodal AI and TL can significantly improve recommendation relevance, reduce cold-start problems, and increase user engagement and conversion rates. Moreover, trust-aware evaluation frameworks such as T-EVAL can guide platform design toward sustainable and ethical AI-driven marketplaces. For *researchers*, this review highlights the need to move beyond accuracy-driven algorithm development toward the design of socio-technical systems. Incorporating fairness, lawfulness, and human-centered evaluation will be essential for the responsible deployment of AI in RE markets.

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