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Conceptual Foundations of Cross-Domain Recommender Systems: An Ontological Perspective

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Abstract

This paper presents a comprehensive synthesis of research on Cross-Domain Recommender Systems (CDRS) through the development of an ontological framework that structures and clarifies the core concepts, processes, and design choices underlying effective knowledge transfer across domains. Based on a systematic review of 37 peer-reviewed studies, the proposed ontology identifies six fundamental components including domain characteristics, data and preprocessing, knowledge transfer mechanisms, methods and algorithms, evaluation and validation, and application context. The analysis reveals that knowledge transfer mechanisms, including entity-based, pattern-based, and feature-based paradigms, play a central role in addressing data sparsity and cold-start problems, with their effectiveness strongly influenced by domain similarity and data availability. The study further highlights the evolution of CDRS methodologies from traditional matrix factorization techniques to advanced deep learning and graph-based models, demonstrating how increased model expressiveness improves cross-domain representation learning under appropriate data conditions. Evaluation practices are shown to be shifting from single-metric accuracy assessments toward multi-objective frameworks that incorporate ranking quality, coverage, and user-centric measures. Building on these findings, this paper translates the proposed ontology into a practical decision framework that guides practitioners in selecting suitable transfer strategies, algorithms, and evaluation metrics based on domain characteristics and system constraints. Overall, this work contributes a unified conceptual foundation and actionable guidance for advancing CDRS research and deployment across diverse real-world application domains.

Keywords:
Cross-Domain Recommendation, Characteristics, Knowledge Transfer, Ontology.

1. Introduction

Recommender systems play a central role in modern digital platforms by supporting users in navigating large volumes of information and making personalized decisions. Traditional recommender systems typically operate within a single domain, such as movies, music, or e-commerce, relying heavily on historical user–item interactions. However, these single-domain approaches often suffer from data sparsity, cold-start problems, and limited user profiles, which restrict their ability to deliver accurate recommendations. Cross-domain recommender systems (CDRS) address these limitations by transferring knowledge across multiple domains, enabling richer user representations and more robust recommendation outcomes. Despite their growing adoption, most existing CDRS research emphasizes algorithmic performance rather than foundational conceptual consistency across domains. This gap motivates the need for a deeper theoretical and ontological understanding of cross-domain knowledge transfer [7], [10], [35].

As cross-domain recommender systems evolve, researchers increasingly adopt advanced machine learning and deep learning techniques to model complex user preferences across heterogeneous domains. Methods based on matrix factorization,

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transfer learning, graph neural networks, and adversarial learning demonstrate promising performance improvements in sparse and non-overlapping settings. Recent studies show that graph-based and deep neural architectures effectively capture latent relationships between domains even when explicit user or item overlap is minimal [8], [11], [12]. However, these methods often operate as black-box models, offering limited insight into how cross-domain knowledge is represented, aligned, and transferred. This lack of transparency raises conceptual challenges, particularly when domain semantics differ significantly, leading to negative transfer and inconsistent recommendation logic [21], [24].

Ontologies provide a formal and explicit specification of concepts, relationships, and constraints within a domain, making them a powerful tool for addressing semantic heterogeneity. In information systems research, ontological modeling supports shared understanding, semantic interoperability, and knowledge reuse across systems. Prior work highlights the effectiveness of ontological approaches in structuring complex knowledge spaces, including learning systems and Internet of Things environments, where semantic consistency is essential [1], [2]. By defining domain concepts and their interrelations at an abstract level, ontologies offer a principled mechanism to bridge semantic gaps between domains. This capability is particularly relevant for cross-domain recommender systems, where misaligned domain semantics often undermine recommendation quality and interpretability.

From a philosophical and epistemological perspective, ontology concerns the nature of entities and their relationships, providing a foundational framework for knowledge representation. Studies in ontology and epistemology emphasize that conceptual clarity directly influences how systems reason, infer, and generalize knowledge [3], [4], [5]. In the context of recommender systems, this implies that poorly defined domain concepts can lead to ambiguous preference modeling and inconsistent recommendations. Applying ontological reasoning to cross-domain recommendation allows researchers to explicitly model user interests, item attributes, and domain relationships, thereby reducing semantic ambiguity and enhancing reasoning transparency. Yet, current CDRS literature rarely integrates formal ontological foundations into system design.

Existing cross-domain recommender approaches primarily focus on statistical correlations rather than semantic alignment. Techniques such as canonical correlation analysis, latent factor alignment, and auxiliary domain learning attempt to map user preferences across domains using shared latent spaces [25], [29], [30]. While effective in many scenarios, these methods often assume implicit semantic compatibility between domains, which may not hold in practice. As domains grow increasingly diverse, such assumptions become fragile, leading to unstable transfer and reduced generalizability. An ontological perspective can address this limitation by explicitly modeling domain similarities, constraints, and hierarchical relationships, enabling more reliable and explainable cross-domain knowledge transfer [16], [26], [45].

Recent advancements further expand cross-domain recommender systems toward context-aware, trust-aware, and privacy-preserving frameworks. Context-aware models incorporate temporal, spatial, and situational information to refine recommendations, while trust-aware systems integrate social and behavioral trust signals to improve personalization [15], [23], [43]. At the same time, federated and privacy-preserving learning approaches aim to enable cross-domain collaboration without direct data sharing [17]. Although these directions enhance system robustness and ethical compliance, they also increase conceptual complexity. Without a unifying ontological foundation, integrating context, trust, and privacy across domains risks conceptual fragmentation and inconsistent system behavior.

Moreover, the emergence of generative and multimodal approaches introduces additional challenges for conceptual coherence. Techniques such as generative adversarial networks, synthetic data generation, and multimodal domain adaptation expand the scope of cross-domain recommendation by addressing data imbalance and representation gaps [14], [37], [44]. While these methods improve performance, they further abstract domain knowledge into latent representations, making semantic interpretation more difficult. Ontological modeling can complement these advanced techniques by grounding latent features in explicit domain concepts, thereby supporting interpretability, accountability, and system validation in complex recommendation scenarios [36], [40].

Given these challenges, this systematic literature review adopts an ontological perspective to examine the conceptual foundations of cross-domain recommender systems. This paper synthesizes existing research to identify how domains, users, items, and relationships are modeled, transferred, and interpreted across systems. By integrating insights from recommender system research, ontology theory, and knowledge representation, this study aims to clarify conceptual gaps, highlight recurring patterns, and propose directions for ontology-driven cross-domain recommendation design. Ultimately, this work seeks to support the development of more semantically coherent, explainable, and robust cross-domain recommender systems [27], [40], [46].

2. Related Works

Early studies on recommender systems primarily focused on single-domain collaborative filtering and content-based methods, which demonstrated strong performance when sufficient user–item interaction data were available. Fernández-Tobías et al. showed that incorporating auxiliary user information, such as personality traits, could mitigate cold-start issues in collaborative filtering systems [7]. While this work highlighted the importance of enriching user representations, it remained constrained within a single domain and did not address semantic inconsistencies that arise when knowledge is transferred across heterogeneous domains. This limitation later motivated the exploration of cross-domain approaches capable of leveraging auxiliary data sources more effectively.

Research on cross-domain collaborative filtering initially investigated the effects of data sparsity and overlap between domains. Hwangbo and Kim empirically analyzed how varying levels of user and item overlap influence cross-domain recommendation performance [10]. Their findings demonstrated that higher overlap generally improves accuracy, but real-world systems often operate with limited or no overlap. Although this study provided valuable empirical insights, it treated domains as statistically related spaces rather than semantically distinct entities, leaving the issue of conceptual alignment between domains largely unaddressed.

Matrix factorization-based approaches became a foundational technique for cross-domain recommendation due to their ability to model shared latent factors. Hashemi and Rahmati applied generalized canonical correlation analysis to align latent representations across domains [25]. Similarly, Yu et al. proposed expanding user and item features via auxiliary domain latent spaces to enhance recommendation accuracy [29]. These methods achieved notable performance gains; however, they relied on implicit latent mappings that lacked semantic interpretability, making it difficult to explain how knowledge was transferred or why certain recommendations were generated.

To overcome the limitations of shallow latent models, researchers increasingly adopted deep learning architectures for cross-domain recommendation. Liu et al. introduced a deep adversarial and attention-based network that learned transferable representations across domains [11]. This approach demonstrated strong performance under sparse conditions and reduced negative transfer. Despite these advantages, the model functioned as a black box and offered limited insight into how domain-specific semantics were preserved or transformed, raising concerns about transparency and conceptual soundness in complex recommendation scenarios.

Graph-based methods further advanced cross-domain recommendation by explicitly modeling relational structures among users, items, and domains. Khan et al. proposed a metadata-driven graph convolutional network to capture cross-domain dependencies [8], while Natarajan et al. integrated linked open data to enhance semantic relatedness in matrix factorization models [9]. These approaches showed that graph structures could encode richer relational knowledge; however, they often depended on externally defined metadata or datasets and did not formalize domain semantics through explicit ontological constructs, limiting their generalizability across diverse application contexts.

Several studies addressed the challenge of non-overlapping domains, where users or items do not appear across domains. Liu et al. leveraged graph neural networks to extract latently overlapping users in such scenarios [12], and Zhang et al. applied domain adaptation techniques to enable recommendation without shared entities [24]. While these methods effectively reduced dependency on direct overlap, they relied heavily on learned representations rather than conceptual mappings, making it difficult to ensure semantic consistency or explainability in cross-domain knowledge transfer.

Context-aware and trust-aware cross-domain recommender systems extended the scope of recommendation by incorporating situational and social factors. Véras et al. proposed CD-CARS, which integrated contextual information across domains [15], while Xu et al. exploited trust and usage context to enhance cross-domain recommendations [16]. These approaches demonstrated improved personalization and robustness; however, they introduced additional layers of complexity without providing a unified conceptual framework to manage heterogeneous contextual and trust-related semantics across domains.

Recent studies emphasized privacy-preserving and federated learning approaches to cross-domain recommendation. Goyal et al. introduced a hybrid federated transfer learning framework that preserved user privacy while enabling cross-domain knowledge sharing [17]. Although this work addressed critical ethical and regulatory concerns, it focused primarily on model-level mechanisms and did not explore how domain knowledge could be semantically aligned or represented in a shared conceptual space, which remains essential for meaningful cross-domain reasoning.

The growing adoption of generative and multimodal approaches further expanded the capabilities of cross-domain recommender systems. Ayemowa et al. examined the role of auxiliary information in generative AI models for cross-domain recommendation [14], while Nguyen et al. proposed synthetic data generation to support cross-domain services [44]. These methods improved data availability and model robustness but further abstracted domain knowledge into latent representations, exacerbating the challenge of semantic interpretability and conceptual grounding.

Despite extensive progress in algorithmic design, only limited work explicitly addresses the ontological foundations of cross-domain recommender systems. Ontology-driven approaches in related fields demonstrate that formal concept modeling enhances semantic interoperability and reasoning [1], [2]. However, systematic integration of ontological perspectives into CDRS remains underexplored. Existing reviews and surveys primarily categorize methods based on algorithms rather than conceptual structures [40]. This gap highlights the need for a comprehensive examination of cross-domain recommender systems from an ontological perspective, which this paper aims to address by synthesizing conceptual, methodological, and semantic insights across the literature.

3. Proposed Method

In this study, we utilize the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to construct a transparent, systematic, and reproducible procedure for selecting journal papers relevant to cross-domain recommender systems (CDRS). We adopt PRISMA to ensure methodological rigor in the identification, screening, eligibility assessment, and inclusion of prior studies, thereby reducing selection bias and improving the reliability of the review outcomes. By applying this established protocol, this paper ensures that the review process remains traceable and that each decision in the literature selection pipeline is well documented and justifiable within the context of a systematic literature review.

We conduct the literature search using the Scopus database, which we selected due to its broad coverage of high-quality, peer-reviewed journals in computer science and information systems. In this study, we retrieve publications published between 2015 and 2025 to capture both foundational works and recent advances in CDRS research. This temporal range allows us to analyze the evolution of cross-domain recommendation techniques, identify emerging trends, and maintain continuity with prior scholarly contributions in this rapidly developing research area.

We construct a comprehensive search query by applying a carefully designed combination of Boolean operators and keyword groups. This paper utilizes multiple terminological variants related to cross-domain settings, recommender system paradigms, personalization strategies, and performance evaluation to ensure broad coverage of relevant studies. The complete search string integrates terms such as "cross-domain," "multi-domain," and "inter-domain" with recommendation-related concepts, system architectures, filtering approaches, user modeling, and evaluation metrics. We adopt this multifaceted strategy to minimize the risk of excluding relevant studies due to vocabulary variations across research communities.

Using the defined search strategy, we initially identify 188 potentially relevant publications. In the first screening stage, we filter studies based on publication type and subject area, retaining only peer-reviewed journal articles indexed within the computer science domain. This paper applies this criterion to ensure academic quality and methodological consistency, which reduces the initial pool to 72 articles. We exclude conference papers, book chapters, and non-peer-reviewed sources at this stage to maintain a focused and high-quality dataset for analysis.

In the second screening stage, we perform a more detailed relevance assessment by examining the titles and abstracts of the remaining articles. In this study, we use this step to evaluate whether the papers explicitly address cross-domain recommender systems or closely related methodological challenges. As a result of this scrutiny, 54 articles satisfy the topical relevance requirements and proceed to the full-text review stage. This step allows us to efficiently narrow the candidate set while preserving studies that potentially contribute meaningful insights to the research objectives.

We then conduct a comprehensive full-text assessment as the third screening stage, where we evaluate each article against predefined inclusion criteria. This paper includes studies that (1) propose methodological or theoretical contributions to cross-domain recommendation, (2) address core challenges such as data sparsity, negative transfer, or knowledge transfer across domains, and (3) are published in English in peer-reviewed journals. Following this rigorous evaluation, we identify 37 articles that meet all inclusion criteria and qualify for systematic data extraction and analysis.

Finally, we perform structured data extraction on the selected studies to identify key ontological components, conceptual frameworks, and methodological patterns underlying CDRS research. This systematic approach supports analytical consistency and strengthens the reproducibility of the study. By clearly documenting each stage of the selection process and the associated criteria, this paper provides a transparent methodological foundation that future researchers can replicate or extend when conducting systematic reviews in the domain of cross-domain recommender systems. This systematic method helps maintain rigor throughout the article selection process and supports the reproducibility of this study. It provides a clear structure for documenting decisions made during identification and screening.

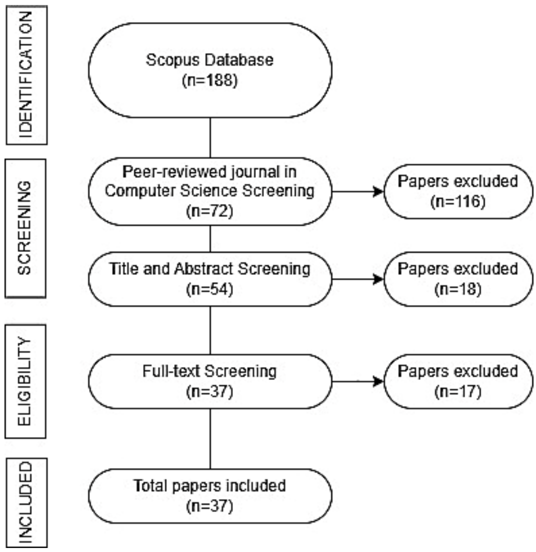

Fig. 1. PRISMA flow diagram for article selection

Fig. 1 presents the PRISMA flow diagram that summarizes the systematic procedure used to identify, screen, and select relevant articles for this study on cross-domain recommender systems. In the identification phase, we retrieve an initial set of 188 publications from the Scopus database using a carefully designed search query. This stage aims to ensure broad coverage of the research domain by capturing studies that potentially address cross-domain recommendation concepts, methodologies, and evaluations. At this point, no exclusions are applied beyond the database scope, allowing the study to begin with a comprehensive pool of candidate articles.

In the screening phase, we refine the initial dataset by applying publication-type and subject-area criteria. We retain only peer-reviewed journal articles within the computer science domain, which results in 72 remaining papers and the exclusion of 116 publications that do not meet these criteria. We then conduct title and abstract screening to assess topical relevance more closely. This step focuses on identifying studies that explicitly address cross-domain recommender systems or closely related problems. As a result, 18 additional papers are excluded, and 54 articles proceed to the eligibility assessment stage.

In the eligibility and inclusion phases, we perform a full-text review of the remaining 54 articles to evaluate their methodological relevance and conceptual contribution. We apply predefined inclusion criteria, which require studies to propose or analyze cross-domain recommendation approaches, address key challenges such as data sparsity or knowledge transfer, and be written in English. Through this rigorous assessment, 17 articles are excluded due to insufficient relevance or methodological alignment. Finally, 37 articles satisfy all criteria and are included in the systematic literature review. This structured selection process enhances the transparency, rigor, and reproducibility of the study.

In this study, we conduct Ontology development followed a systematic two-stage process: (1) component identification, where repeated reading of all 37 articles extracted recurring concepts, terminologies, and structural elements constituting CDRS frameworks, including methodological approaches (matrix factorization, deep learning, graph neural networks), knowledge transfer paradigms (entity-based, pattern-based, feature-based), data characteristics (sparsity levels, domain types, overlap patterns), and evaluation strategies (metrics selection, validation approaches), and (2) taxonomy construction, which organizes identified components into hierarchical categories with domain characteristics, transfer mechanisms, data properties, methods, evaluation, and applications as top-level nodes.

4. Result and Discussion

A. Ontological Framework of CDRS: Core Conceptual Components

A comprehensive ontology for CDRS systematically organizes the fundamental concepts, processes, and relationships that govern knowledge transfer across domains to generate personalized recommendations. Based on the review of 37 studies, six key elements were identified: Domain Characteristics, Data and Preprocessing, Knowledge Transfer Mechanisms, Methods and Algorithms, Evaluation and Validation, and Application Context. These form a layered architecture that integrates the theoretical and practical perspectives of cross-domain recommendations. The presented ontology explains how domain alignment, data properties, and transfer mechanisms contribute to system performance and should provide both a conceptual basis for researchers and a practical framework for finding an effective implementation of a CDRS solution.

Table 1. Taxonomy and functional roles of CDRS components

Component	Description	Role in CDRS
Domain Characteristics	Defines properties and relationships between source and target domains	Establishes the context and constraints for knowledge transfer; determines feasibility and approach for cross-domain recommendation
Knowledge Transfer Mechanisms	Specifies how information flows from the source to the target domain	Core enabler of CDRS; bridges domains to alleviate sparsity and cold-start problems
Data and Preprocessing	Describes data types, characteristics, and preparation steps	Provides raw material for recommendations; data quality directly impacts transfer effectiveness
Methods and Algorithms	Categorizes computational approaches for CDRS	Translates transfer mechanisms into operational systems; determines computational complexity and accuracy
Evaluation and Validation	Defines metrics and methodologies for assessing performance	Measures recommendation quality; guides algorithm selection and optimization
Application Context	Situates CDRS within real-world domains and scenarios	Ensures practical relevance; accounts for domain-specific constraints and user expectations

As illustrated in Table 1, the CDRS ontology provides a structured foundation for organizing and interpreting the key elements required to design, implement, and comprehend a recommender system. These ontological models are useful resources for education and research on developing CDRS. Therefore, the ontological framework plays a vital role in enhancing conceptual understanding, guiding technological development, and supporting practical implementation within these domains. In alignment with this ontology, several core components essential to CDRS are outlined in Fig. 2, and detailed explanations are presented in the next section.

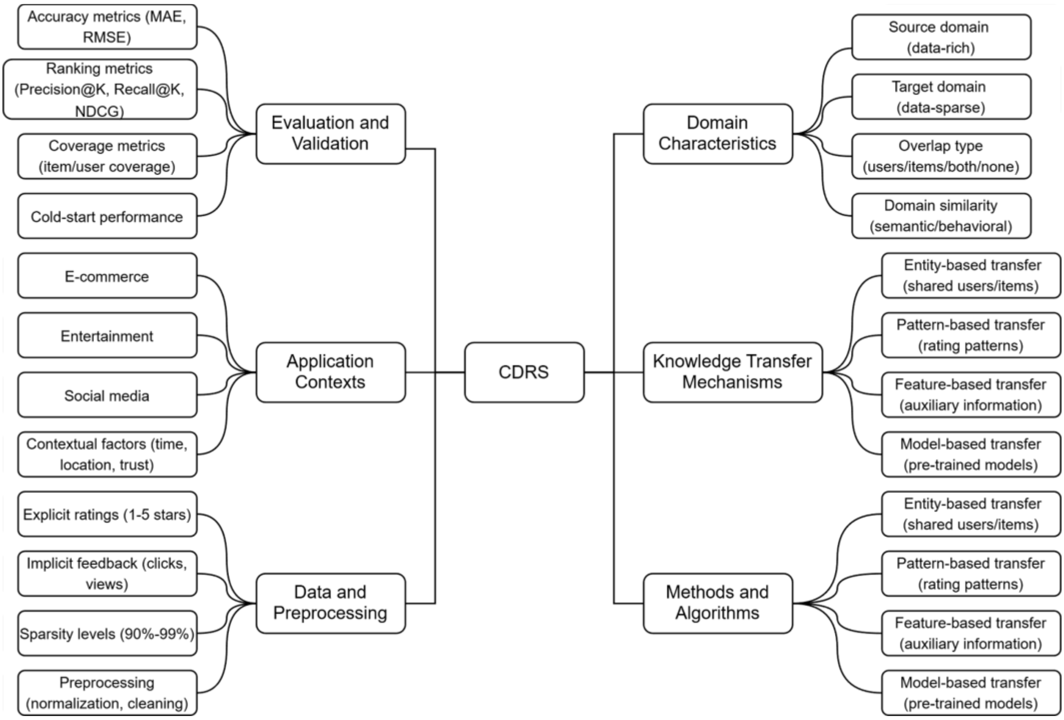

Fig. 2. Conceptual framework of CDRS

B. Understanding Knowledge Transfer Mechanism

CDRS allows knowledge transfer from a source domain with richer data to a target domain with sparser data. Based on a systematic review of 37 articles, three dominant paradigms of knowledge transfer can be identified: (1) entity-based transfer, which leverages shared users or items as bridges to directly map preferences across domains [10], [19], [29], [30]; (2) pattern-based transfer, which extracts and transfers rating patterns or behavioural similarities without requiring explicit entity overlap [21], [31], [32]; and (3) feature-based transfer, which exploits additional information such as reviews, demographics, or semantic attributes to construct domain-independent user and item representations [9], [14], [23], [25], [29], [31], [33], [34], [35], [36].

The intrinsic characteristics of the domains involved determine the applied transfer mechanism. Systems exhibiting considerable user overlap tend to adopt entity-based strategies that establish joint latent factor spaces [11], whereas domains lacking common entities often rely on pattern-based methods, such as cluster-level knowledge sharing or codebook-based transfer [21], [22]. Recent studies have proposed hybrid approaches that integrate multiple paradigms, including adversarial domain adaptation to align cross-domain feature distributions while maintaining discriminative capacity [11], aspect-based sentiment transfer to refine user preference mapping across heterogeneous contexts [31], and graph neural networks that infer latent user correspondences through cross-domain interaction graphs [12].

The success of knowledge transfer depends on the degree of similarity between the domains. Semantically related domains, such as Books and Movies, enable more effective transfer compared to unrelated ones, such as Electronics and Clothing [25], [37].

C. Methods, Data, Evaluation, and Application Domain

CDRS has evolved from traditional matrix factorization to deep learning models that overcome prior constraints. First-generation methods (2015-2018) primarily employed matrix factorization techniques, including Collective Matrix Factorization (CMF), Cross-Domain Tensor Factorization (CDTF), and variations of Non-negative Matrix Factorization (NMF), which decomposed rating matrices to extract shared latent factors across domains [10], [20], [21], [22], [38]. Second-generation approaches (2018-2021) introduced deep learning architectures, autoencoders for robust feature learning under noise [27], deep neural networks for capturing sequential user behaviour patterns [39], and deep matrix factorization combining linear and non-linear transformations, demonstrating superior performance on highly sparse datasets [40]. Third-generation methods (2021-present) leverage advanced architectures, including Graph Convolutional Networks (GCN) that exploit graph topology to learn user-item interaction patterns [8], [12], Transformer-based models that capture long-range dependencies through attention mechanisms [41], [42], and contrastive learning frameworks that maximize agreement between augmented views of the same data while minimizing similarity to negative samples [13], [41], [42].

The most frequently utilized datasets across these studies include Amazon product reviews (Books, Movies, Music, Electronics), MovieLens (1M, 20M, and 25M), Netflix, and domain-specific datasets such as Douban, Goodreads, Epinion, and Ciao for specialized scenarios [8], [12], [25]. Evaluation methodologies predominantly employ accuracy metrics (MAE and RMSE) reported in most studies, ranking metrics (Precision@K, Recall@K, NDCG, and coverage metrics), with recent work advocating for multi-objective evaluation that balances accuracy against diversity, novelty, and serendipity to avoid filter bubble effects [12], [13], [20], [23], [43]. Table 2 provides detailed information on each evaluation metric.

Table 2. Evaluation metrics

Metric	Formula	Variables
MAE	$MAE = \frac{1}{n}\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert$	n: total predictions, y_i: actual rating, $\hat{y}_i$: predicted rating
RMSE	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$	n: total predictions, y_i: actual rating, $\hat{y}_i$: predicted rating
Precission@K	$P@K = \frac{\lvert R_k \cap T_k \rvert}{K}$	R_k: top-K recommendations, T_k: relevant items, K: cutoff
Recall@K	$R@K = \frac{\lvert R_k \cap T_k \rvert}{\lvert T_k \rvert}$	R_k: top-K recommendations, T_k: relevant items, K: cutoff
NDCG@K	$NDCG@K = \frac{DCG@K}{IDCG@K}$ $DCG@K = \sum_{i=1}^{K} \frac{rel_i}{log_2(i+1)}$	rel_i: relevance score at position i, $IDCG@K$: ideal DCG, K: cutoff
Item Coverage	$IC = \frac{\lvert I_{rec} \rvert}{I_{total}}$	I_{rec}: recommended items, I_{total}: all items
User Coverage	$UC = \frac{\lvert U_{rec} \rvert}{U_{total}}$	U_{rec}: recommended users, U_{total}: all users

The CDRS is widely adopted across various sectors, with the majority of studies focusing on e-commerce applications, followed by entertainment, social media, and emerging domains such as tourism, healthcare, and education [8], [26], [30], [44]. In practice, platforms such as Amazon, Netflix, and Spotify use cross-domain signals such as browsing history, viewing habits, and sentiment from user reviews to enhance cross-category and cross-media recommendations [5], [7], [11], [12], [19], [24], [25], [26], [29], [32], [45], [46]. Beyond algorithmic design, factors such as time-dependent user behaviour, geographic and social contexts, and sentiment-based preference cues play an essential role in shaping how effectively CDRS can operate in real-world environments [15], [23], [31], [43].

D. A Practical Guide from Ontology Framework

The proposed ontology is transformed into a practical decision framework that guides CDRS practitioners in aligning system requirements with suitable transfer methodologies. For domains with high user overlap, entity-based transfer using shared latent factor models is most effective, while pattern-based and feature-based approaches are suitable for low-overlap or semantically related domains with rich auxiliary data [9], [11], [26], [31]. Algorithm selection depends heavily on data sparsity. Matrix factorization is robust for extremely sparse data, deep learning captures non-linear patterns in moderately sparse settings, and graph neural networks perform best when the data density is higher [6], [8], [12], [21], [23]. The evaluation should incorporate multiple metrics, including accuracy, ranking, coverage, and business-specific goals, while prioritizing cold-start user performance [7], [13]. By grounding the system design in this ontology, developers can minimize trial-and-error experimentation, ensure theoretically justified model selection, and foster a shared understanding across technical and business teams.

5. Conclusion

This study synthesizes prior research on cross-domain recommender systems into a coherent ontological framework that clarifies the essential components and their functional roles within CDRS design and implementation. By systematically reviewing 37 peer-reviewed studies, we identify six core elements, including domain characteristics, data and preprocessing, knowledge transfer mechanisms, methods and algorithms, evaluation and validation, and application context. This ontology provides both theoretical clarity and practical guidance by explicitly linking domain properties, data quality, and transfer strategies to recommendation performance. As a result, the proposed framework contributes to a unified conceptual understanding of CDRS and addresses the fragmentation that has characterized prior research in this field.

The findings further demonstrate that knowledge transfer mechanisms lie at the core of CDRS effectiveness, with entity-based, pattern-based, and feature-based paradigms each offering distinct advantages depending on domain overlap and semantic relatedness. We show that the choice of transfer mechanism must align with domain characteristics and data availability, as mismatches can limit performance gains or introduce negative transfer. Recent advances, including hybrid and deep learning–based approaches such as graph neural networks, adversarial adaptation, and contrastive learning, significantly enhance transfer capability by modeling complex cross-domain relationships. However, their success remains strongly dependent on domain similarity and data density, reinforcing the need for principled design choices rather than purely empirical trial-and-error development.

Finally, this study translates the proposed ontology into a practical decision framework that supports method selection, evaluation design, and real-world deployment. The evolution from matrix factorization to deep and graph-based models highlights how algorithmic complexity must be balanced against data sparsity and application constraints. Our analysis also emphasizes the importance of comprehensive evaluation strategies that go beyond accuracy to include ranking quality, coverage, diversity, and user-centric outcomes, particularly for cold-start scenarios. By grounding CDRS development in an explicit ontological structure, this work offers a reproducible and systematic guide for researchers and practitioners, facilitating more robust system design, clearer communication across stakeholders, and more effective deployment of cross-domain recommendation solutions in diverse application domains.

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