Cold-Start and Data Sparsity Problems in a Digital Twin based Recommendation System

Flávia Pires*, António Paulo Moreira†, Paulo Leitao*‡

* Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal. Email: {fpires, pleitao}@ipb.pt
† INESC TEC - INESC Technology and Science, Faculty of Engineering, University of Porto, Rua Dr. Roberto Frias, Porto, 4200-465, Portugal. Email: amoreira@fe.up.pt
‡ Laboratório Associado para a Sustentabilidade e Tecnologia em Regiões de Montanha (SusTEC), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal

2024 IEEE 29th International Conference on Emerging Technologies and Factory Automation (ETFA) | 979-8-3503-6123-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ETFA61755.2024.10711105

***Abstract*—The emergence of Digital Twins (DT) in Industry 4.0 has enabled the decision support systems taking advantage of more effective recommendation systems (RS). Despite the RS's growing popularity and ability to support decision-makers, these face two significant challenges, cold-start and data sparsity, which limits the system's capability to provide effective and accurate decision support. This paper aims to address these issues by conducting a literature review, analysing the current research landscape, and identifying the main enabling methods, algorithms, and similarity measures to mitigate these challenges. The performed analysis enables the point out of future research directions for developing effective and accurate RS that empower decision-makers.**

***Index Terms*—Digital Twin, Cold-Start, Data Sparsity.**

I. Introduction

THE Digital Twin is one of the new technologies that emerged within the fourth industrial revolution, supporting the digital transformation and enabling decision support. Decision support is one of the main functionalities of the Digital Twin [1], [2], encompassing capabilities like diagnosis, monitoring, and prognosis. The term *decision support* can be defined as the action of supporting people in making decisions [3]. Within this functionality lies the general discipline of *decision-support systems (DSS)*, which can be defined as an interactive computer-based system with the main purpose of helping decision-makers use data and models to identify and solve problems and make decisions. The DSS comprises various information systems, such as executive information systems, executive support systems, expert systems, and recommendation systems (RS) [3], [4].

RS is a DSS which contributes to aiding decision-makers in selecting relevant options based on their preferences, behaviour, and item data, serving as an intelligent DSS providing personalised recommendations [5], [6]. The RS evolved as an independent research field in the mid-70s, but only in the mid-90s, the first approaches started to appear [7], [8]. Recently, RSs have been widely applied in various applications, from e-commerce to entertainment, demonstrating their potential in enhancing systems performance [9], [10]. The core functionalities of the RS rely on three types of feedback: *explicit*, *implicit*, and *hybrid*. The explicit feedback related to the decision-makers direct communication of their preferences is reliable and transparent, leading to accurate recommendations. The implicit feedback is inferred from the decision-maker's behaviour, making it less precise. Lastly, hybrid feedback combines the two previous feedbacks, potentially enhancing the accuracy of the systems [11].

However, despite the increasing popularity and effectiveness of RS, two significant challenges affect their ability to perform decision-support, the *Cold-Start* and the *Data Sparsity* problems [12]–[15]. The cold-start problem is one of the most common research problems in the RS, defined as when a new user or a new item enters the system and still has no activity, and the system cannot provide recommendations. Data sparsity is the second most common challenge in RS, occurring when the system lacks a sufficient amount of decision-maker feedback to perform recommendations accurately. Both challenges pose serious concerns to the business value of RS since users affect the effectiveness, as well as user adoption and engagement.

While existing research exploring the mitigation of cold-start and data sparsity problems in RS through the proposal of different approaches, this paper aims to contribute to the field by analysing the current scientific landscape through a literature review. This will allow to identify the enabling methods used to address these challenges and establish future research directions based on the state-of-the-art assessment. With this in mind, it was possible to define four main research directions for the mitigation of cold-start and data sparsity related to combining enabling methods, the development of new similarity measures, the application of artificial intelligence (AI) based algorithms, and the explainability of RS.

The paper is organised as follows: Section II provides the context and related work, focusing on recommendation approaches and the key challenges faced by the RS, identifying the challenges that need further research, that is, cold-start and data sparsity. Section III presents a literature review analysis of the recommendation approaches to mitigate the cold-start and data sparsity. Section IV discusses the future research directions for the RS field, focusing on the cold-start and data sparsity problems. Finally, Section V concludes the paper.

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.

II. CONTEXT AND RELATED WORK

The role of DSS within the Digital Twin technology has undergone significant advancements to offer automated, user-centred, and intelligent decision support [1], [2], [4]. The RS falls into the *cooperative* DSS category, enabling the decision-maker cooperation to refine the recommendations [16].

A. Recommendation Systems Approaches

The effectiveness of an RS in making proper recommendations depends on the approaches used to determine items/scenarios that match the user's preferences and needs. Figure 1 illustrates the classification of the recommendation approaches.

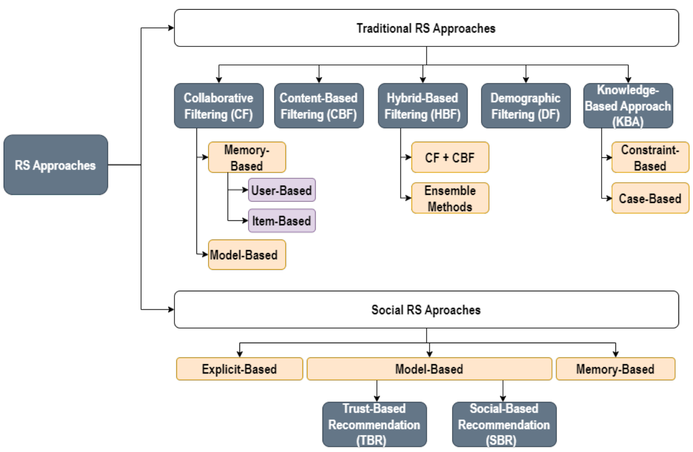

Fig. 1: Classification of RS approaches.

There are two main recommendation approaches: traditional and social. Traditional RS ignores social interactions among users and relies only on rating data. This includes approaches such as *Collaborative Filtering (CF)*, *Content-Based Filtering (CBF)*, *Hybrid Approaches (HA)*, *Demographic Filtering (DF)*, and *Knowledge-Based Approach (KBA)*. On the other hand, social RS uses measurable social networks or relationships, combining rating, trust, and social data, to make recommendations, being one of the approaches the *Trust-based Recommendation (TBR)* [8].

The CF approach is a popular and well-established technique used to generate recommendations, and its operation is based on users who share similar interests in one domain, who will likely have similar preferences in other domains. There are two main categories, the *Memory-based CF* and *Model-based CF*. Memory-based CF uses the rating matrix and similarity measures to generate recommendations, while Model-based CF relies on a mathematical model to predict user ratings. Memory-based CF can be further divided into two categories, the *User-based CF*, which recommends similar items based on similar user preferences, and *Item-based CF*, which recommends similar items based on past user preferences [5]–[8].

The CBF approach is a straightforward recommendation model based on unique features or attributes of the items to make recommendations. This approach employs two techniques: classifier-based and neighbour methods. The classifier-based method uses a classifier to evaluate an item's content and determine whether or not it should be recommended. Meanwhile, the neighbour method creates a network of items based on rated items to uncover user interests [6]–[8], [17].

The HA approach was developed to overcome the scalability and sparsity limitations of CF and CBF, by combining multiple approaches to yield superior recommendation performance. Seven hybridisation techniques exist, including weighted hybridisation, switching hybridisation, and cascade hybridisation, among others [5], [6].

The DF approach uses the user's attributes, e.g., age, gender, address, education, and employment, to make recommendations based on the demographic classes. This considers the common or similar personal attributes between users to infer these are likely to have preferences for similar users [17], [18].

Lastly, the KBA approach is domain-specific and uses explicit or domain knowledge from the users to produce personalised recommendations. To perform recommendations, it is possible to employ three types of knowledge: about the users, the items, and the matching between them. One of the main advantages of this approach is that it does not suffer from ramp-up/cold-start and rating sparsity problems [18].

The social RS operates on social networks founded on trust, friendship, membership, and following relationships. These RS can be classified into three categories: *Explicit-Based*, *Memory-Based*, and *Model-Based*. Explicit-based methods are dependent on explicit user connections on social media, while memory-based methods use memory-based CF models to obtain missing ratings. The model-based methods, on the other hand, use matrix factorisation, and the fundamental idea is that socially connected users influence user preferences [19].

The TBR approach has proven to be a highly effective social RS, utilising trust as a mean of measuring user relationships [19], [20]. In dynamic and decentralised environments, trust is an essential factor in the decision-making process [21]. Trust can be categorised into two distinct types, *context-specific interpersonal*, which is the user trust in another user regarding a specific situation, and *system-impersonal*, which describes the user trust over the system itself [22]. This approach uses trust-related information to generate individual recommendations, taking into account the trustworthiness and reliability of users, items, and other entities involved. Trust information is extracted from social trust networks created by users. By using trust in recommendation approaches is possible to build new user relationships, increase connectivity, and solve challenges such as data sparsity and cold-start [5], [8], [23].

Table I compares the advantages and disadvantages of the presented RS approaches.

CF is a good approach when there's a lot of data, but it struggles when recommending new users or items or when there are not many user ratings. CBF can recommend even without ratings, but it needs detailed descriptions of the items. This approach also has trouble recommending for new users or

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.

TABLE I: Advantages and disadvantages of each recommendation approach (adapted from [8]).

	Approach	Advantages	Disadvantages
Traditional	CF	Very easy to implement and understand New data added easily High quality recommendation in social networks Independent from the item content No over-specialisation problem Domain-independent approach	Highly dependent on user ratings Suffers from new-user and new-item cold-start problem Poor performance for sparse data Limited scalability for large datasets Limited recommendation diversity Prone to shilling attacks
Traditional	CBF	User independence Transparency on recommendation explanation Good at recommending new items No dependency on historical user-items interactions Recommendation quality increases over time, and user usage	Harder to have feedback from the users Overspecialisation problem Difficult to generate attributes for items Suffers from new-user cold-start knowledge of the field is often necessary
Traditional	HA	Mitigates limitations of CF and CBF Better prediction performance Combines strengths of different approaches Provides diverse and balanced recommendations	Costly implementation Increased implementation complexity Difficult to provide a recommendation explanation Hard to compare recommendation approaches
Traditional	DF	Personalisation based on user demographics Provides targeted recommendations for user No historical data and simple to implement	Security and privacy of the user data General and low-quality recommendations Low adaptability to user changes
Traditional	KBA	Does not have a ramp-up problem User independent Sensitive to preference changes	Complex knowledge engineering Recommendation performance is static Limited scalability and adaptability to new domains
Social	TBR	Alleviation of data sparsity and cold-start Increase recommendation coverage and predictive accuracy based on the number of users	Limited for the new item cold-start problem Accuracy can decrease depending on the number of connections to the source user

those whose preferences change quickly. HA combines CF and CBF to tackle cold-start, data sparsity, and overspecialisation. However, it can be complex to set up and explain. The DF approach uses user demographic information to make recommendations. It is easy to implement but requires personal information and might lead to generic recommendations. In the case of the KBA approach, it does not rely on user ratings, but it requires a lot of work to set up the knowledge base. This approach also does not offer much exploration of different options. Lastly, the TBR improves accuracy by considering trust between users; however, it struggles with defining trust networks and recommending new items.

B. Key Challenges of Recommendation Systems

Although the RS are widely used to provide personalised recommendations in various fields, e.g., e-commerce, health, and entertainment, these still present significant challenges. The general challenges associated with the traditional and social RS approaches are as follows:

- *Cold-start:* relates to the lack of data on the new users and new items in the RS and the inability to perform accurate and reliable recommendations. This is the most common problem in RS, which can be divided into three categories: *New Community/System*, *New Item*, and *New User*. The new community category refers to the moment when a new system is launched and does not have historical data from which it is possible to perform reliable recommendations. The new item type refers to introducing new items into the RS from which relevant content information is available, but there is no rating information. Lastly, the new user problem considers the scenario where new users are introduced to the RS and do not have information about interactions and rating history. All these problems make it very difficult to generate personalised recommendations [7], [24], [25].
- *Data sparsity:* the dataset used in the RS lacks sufficient data to accurately identify similar users or items, negatively affecting the recommendations' quality. This is a common challenge faced by RS that rely on peer feedback. It is difficult to ensure that users rate enough items during the recommendation process to guarantee that their preferences are identified [24], [26].
- *Scalability:* as more users and items are added, the data input for RS grows quickly. To keep users engaged, the RS needs to respond quickly, which is the main challenge in designing efficient algorithms for small and large-scale datasets. The availability of large amounts of information has made this more difficult, leading to computation difficulties for RS algorithms [24], [26], [27].
- *Diversity:* the system can suggest similar and contrasting items. The current approach may limit users' choices and disregard other viable alternatives. This issue presents a two-fold challenge, as prioritising diversity can potentially lead to decreased accuracy. Two metrics assessing this problem are *surprisal* and *personalisation*. This matter is of significance as it avoids the prevalence of popularity bias [24], [26].
- *Privacy:* the recommendation process involves gathering and retaining user data to create customised recommendations. Given the sensitive nature of this information, privacy measures are imperative. These measures can be either interactive, allowing users to request and receive

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.

data, or non-interactive, using a streamlined version of the data for future operations [27]
- *Shilling attacks:* the vulnerability to manipulation by malicious entities who inject fake or biased data. These manipulations are carried out through ”profile injection” attacks, which rely on fake profiles to provide fraudulent item ratings. Two types of attacks exist: push and nuke. Push attacks artificially increase the popularity of an item, while nuke attacks decrease it [7], [28].
- *Accuracy:* the capacity to accurately predict and recommend relevant items to the users based on their feedback and preferences. Factors like data sparsity, cold-start, data quality, and scalability make it difficult to achieve that. Improving the RS’s accuracy can lead to higher user satisfaction and engagement [24], [26].
- *Structured recommendations:* the capability of an RS to predict preference for sets of items. This includes two challenges: first, the number of possible sets grows exponentially with the group size, and second, selecting the right score function for sets is unclear. This challenge arises due to the need to incorporate additional constraints and consider complex item relationships [27].
- *Trust:* being able to establish and maintain trust between the users and the RS. This involves the users’ perceptions, beliefs, confidence, reliability, fairness, and credibility of the recommendations provided by the system. Trust in the system can be influenced by several factors, including transparency and explainability of the algorithms, trust in other users of the system regarding their reputation and credibility, and social factors [20], [29].

as previously referred, two of the main challenges that any RS faces are the *cold-start* and *data sparsity* problems, which require further research on efficient mitigation methods.

III. Review on Cold-Start and Data Sparsity

Understanding the current scientific landscape, the existing approaches, and their limitations are essential for addressing the cold-start and data sparsity challenges.

A. Scientific Landscape

The bibliometric study follows the methodology established in [30] with the following search query:

TITLE-ABS-KEY(”cold-start” OR ”cold start”) AND (”data sparsity” OR ”spars”) AND (”recommendation system” OR ”recommender system”) AND PUBYEAR > 1999 AND PUBYEAR < 2024*

Based on the performed query in the Scopus database, 1.430 publications were identified, supposedly focusing their research on the cold-start and data sparsity problems for RS. Considering only the English-written publications and those in the final publication stage, the final dataset has 1.352 publications. Figure 2 illustrates the evolution of publication classes and numbers over the timespan specified in the search query based on this dataset of 1.352 documents.

The number of publications on the topic became more prominent after 2009, showing a higher number regarding conference papers, which was only surpassed in 2021 by

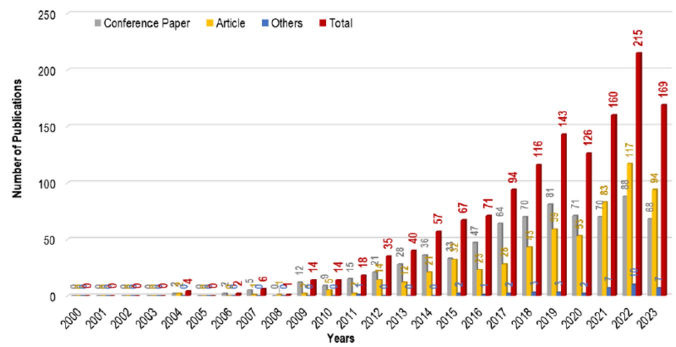

Fig. 2: Evolution of publication classes and numbers.

journal publications. This can have two possible justifications, the first being a direct consequence of the COVID-19 pandemic since this led to a shift in the publication strategies of most research groups, and the second is directly linked to the increase of the maturity of the research to be carried out on these topics. Since 2018, the number of publications on these challenges has stabilised. However, in the last two years, the number of publications significantly increased, demonstrating that the interest in mitigating these problems is still relevant for the research community. The high number of journal publications may be due to the recent growing importance of RS in various sectors (e.g., e-commerce, streaming services, and social media), so it is vital to address challenges like cold-start and data sparsity.

To assess the patterns, trends, and relationships within the research domain of the cold-start and data sparsity challenges, an author keywords co-occurrence network was generated in the VOSviewer software and presented in Figure 3.

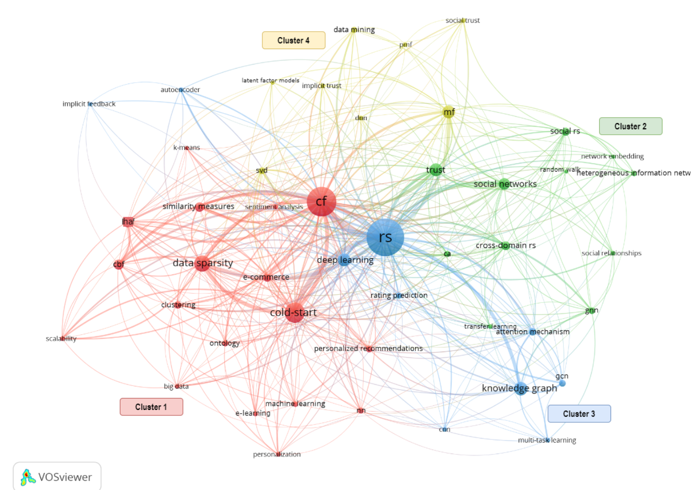

Fig. 3: Authors keywords co-occurrence network of the literature on cold-start and data sparsity problems in RS (Timeframe 2000-2023; *n*= 2044 keywords; threshold of 10 occurrences per keyword, display 47 keywords), with four clusters.

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.

This author keyword co-occurrence network showcases four distinct clusters, each revolving around a main topic: *'RS'*, *'CF'*, *'cold-start'*, and *'data sparsity'*. In Cluster 1 (Red), the challenges are identified as the *'cold-start'*, *'data sparsity'*, and *'scalability'*, alongside two proposed RS approaches to mitigate these challenges *'HBF'* and *'CBF'*. Cluster 2 (Green) focuses on mitigation techniques focusing on *'social RS'*, while Cluster 3 (Blue) highlights AI-based algorithms. Throughout the network, a range of algorithms like *'k-means'*, *'SVD'*, *'autoencoder'*, *'transfer learning'*, *'cnn'*, *'gcn'*, and *'knowledge graph'* were identified as mitigation measures. Lastly, Cluster 4 (Yellow) identifies the conjugation of *'social trust'* with approaches based on *'MF'* (matrix factorisation), *'PMF'* (probabilistic matrix factorisation), and also including *'implicit trust*. There are noticeable patterns in the network, such as the application of AI-based algorithms, the use of similarity measures, and trust relations/metrics to mitigate the cold-start and data sparsity challenges.

B. Literature Review

Upon performing a high-level assessment of the dataset of 1.352 publications from the Scopus database, several studies were identified that could help to mitigate the challenges of cold-start and data sparsity. The reviews and theoretical publications were removed (removing 19 publications) since the focus of this study is to assess experimental approaches that address these challenges. The scope in terms of timespan was also narrowed towards more recent publications, focusing on publications between 2013 and 2023 (removing 94 publications), resulting in 1239 publications. Only the journal publications were considered (removing 693 publications), resulting in 546 publications. From this resulting dataset, a targeted selection was performed, ensuring a diverse coverage of mitigation approaches, methodologies, and techniques, capturing recent advancements and trends within the specific time span. It was also taken into consideration the publications that include the baseline methods (e.g., MoleTrust, SoRec, SVD++, TrustWalker, RSTE, SocialMF, SoReg, TrustSVD, TrusPMF) for handling the cold-start and data sparsity, resulting in the assessment of 25 publications. Table II presents the characterisation of the approaches that mitigate cold-start and data sparsity challenges.

The most commonly used approaches for mitigating these challenges are HA and TBR, followed by CF. Recently, the CA approach has also emerged. Most of the approaches analysed in this study focus only on the cold-start problem (12 publications), leaving approaches that try to mitigate both problems in second place (8 publications) and those that focus only on the data sparsity problem in last place (5 publications).

Several strategies have been proposed based on similarity measures, including measures such as Proximity-Impact-Popularity (PIP) and Proximity-Significance-Singularity (PSS) [32], [41], random walk methods using PCC [34], social network-based approaches [36], an SVD++ algorithm with explicit and implicit feedback [42], dual regularisation [43], and decoupling mechanisms exploiting similarity [45]. Other strategies include probabilistic interpretation of user trust, deep network model, semantic features, and topic embedding and contextual information [14], [46], [47], [51]. Clustering and association rule mining have also been used to extract frequent patterns [52].

To mitigate the data sparsity problem, researchers have explored various approaches, such as using social networks and factoring in trust relationships [19], [35], incorporating social network data as regularisation [37], using AI-based algorithms as a memetic algorithm with visual clustering [39], and adopting an ontology-based clustering approach [49].

Measures as trust networks [31], AI-based algorithms [33], and combining CF with similarity measures and social networks [38], [40], [44] are being used to mitigate the cold-start and data sparsity problems together. Other approaches being used are merging explicit and implicit data through similarity, clustering techniques, and association rules [48], reducing the neighbourhood before computing similarity and predicting [50]. Lastly, similarity measures are combined with SVD and contextual information [53].

All the presented approaches were evaluated offline using existing online datasets, e.g., Epinons, FilmTrust, Douban, CiaoDVD, MovieLens, Yahoo, Flixter, and Yelp. The entertainment domain, including movies, music, and books, is most commonly used for validation, followed by e-commerce and service recommendations, while the least explored domain is manufacturing. Regarding the evaluation metrics, most approaches use measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Precision, Recall, F-measure, and Coverage.

From the identified approaches, the mitigation of the cold-start problem primarily focuses on the improvement of similarity measures, often complemented by AI-based algorithms. In the case of approaches for handling data sparsity, most use techniques based on social networks with trust relationships, integrating similarity measures and intelligent algorithms.

Initial approaches tackled these challenges individually, emphasising trust, similarity, or intelligence. Currently, the approaches are more complex, combining two or three methods to attain better results. In particular, some authors, like [44] and [49], propose comprehensive approaches that combine the three enabling methods, trust, similarity, and intelligence. Trust-based mechanisms employ user social trust networks, similarity measures identify patterns in sparse data, and AI-based algorithms extract insights from user interactions. By integrating these techniques, RS can effectively address the cold-start problem and data sparsity, enhancing robustness and efficiency.

Consequently, several research gaps were identified from this analysis of the state-of-the-art literature, such as (1) unexplored possibilities of combining different techniques inside the general enabling methods (i.e., trust, similarity and intelligence) that can surpass the existing approaches, (2) the development and innovation of new similarity measures combined with AI-based algorithms, (3) the application and exploration of RS in the field of manufacturing and services,

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.

TABLE II: Characterisation of recommendation approaches focusing on mitigating cold-start and data sparsity challenges. (**Symbol Caption:** if the challenge is addressed arises a ✓, if the enabling method is used to mitigate the challenge arises a △, lastly to identify the application domain is used a ⋈)

				Challenges		Enabling Meth.			Domain			
Ref.	**Approach**	**Name**	**Summary**	**Cold-Start**	**Data Sparsity**	**Trust**	**Intelligence**	**Similarity**	**E-commerce**	**Entertainment**	**Manufacturing**	**Service**
[31]	TBR	MoleTrust	Trust-aware RS using local trust metrics to improve accuracy and coverage for cold-start users.	✓	✓	△			⋈			
[19]	CF	SoRec	A factor analysis approach based on probabilistic matrix factorisation using users social network and ratings information.		✓	△				⋈		
[32]	CF	–	Introduces a new heuristic similarity measure focusing on addressing cold-start users.	✓				△		⋈		
[33]	CF	SVD++	Extends the latent factor and neighbourhood models in CF, using explicit/implicit feedback.	✓	✓		△			⋈		
[34]	TBR	TrustWalker	A random walk model that combines trust-based and CF approaches, focusing on cold-start users.	✓		△		△	⋈			
[35]	TBR	RSTE	Probabilistic factor analysis framework, combining users' tastes and trusted friends preferences.		✓	△			⋈			
[36]	TBR	SocialMF	A model using social network and matrix factorisation, focusing on trust propagation and cold-start users.	✓		△			⋈	⋈		
[37]	TBR	SoReg	Matrix factorisation with social regularisation, incorporating social network information.		✓	△		△	⋈			
[38]	CF	–	Combine social network and CF techniques.	✓	✓			△			⋈	⋈
[39]	HA	–	A memetic algorithm combined with visual clustering.		✓		△		⋈			
[40]	TBR	Merge	Incorporate social trust information into CF, demonstrating improved accuracy and coverage.	✓	✓	△		△	⋈	⋈		
[41]	CF	NHSM	New similarity model considers local context information and global user behaviour preferences.	✓				△	⋈	⋈		
[42]	TBR	TrustSVD	A trust-based matrix factorisation model with explicit and implicit influence of user trust and item rating.	✓		△	△		⋈	⋈		
[43]	HA	DualDS	A discriminative selection with dual regularisation, utilising category labels, and exploring the correlation between users and items.	✓			△			⋈		
[44]	CF	DGCTARS	A graph-clustering algorithm, incorporating trust statements.	✓	✓	△	△	△	⋈			
[45]	HA	DecRec	A matrix completion model, decoupling the completion of a submatrix and transduction of knowledge to prevent error propagation.	✓				△		⋈		
[46]	TBR	TrustPMF	A probabilistic interpretation of TrustMF model, to incorporate user's browsing behaviours to infer preferences.	✓		△				⋈		
[47]	HA	MFUIpT	A coupled deep network model for fusing heterogeneous modalities by integrating content and rating information.	✓			△			⋈		
[48]	HA	–	Uses association rules for improving accuracy.	✓	✓		△	△		⋈		
[49]	TBR	–	A ontology-based clustering approach.		✓	△	△	△				⋈
[50]	CF	CRCF	Covering neighbourhood reduction in user-based CF.	✓	✓			△		⋈		
[14]	CF	RS-LOD	Enhance matrix factorisation with implicit feedback and linked open data.	✓				△		⋈		
[51]	HA	RecTEC	Use rating data and topic embedding and incorporate into user-based CF.	✓				△	⋈			
[52]	HA	–	Uses clustering and association rule mining for cold-start users.	✓			△			⋈		
[53]	CA	CSSVD	Context-aware RS enhancing accuracy and relevance of recommendations.	✓	✓		△	△		⋈		

(4) the exploration of the possibility of having adaptive approaches, being able to adapt the recommendation algorithm or similarity measure according to the presented situation, and (5) even though the research on mitigating both problems, cold-start and data sparsity, is starting to grow there is still space for further exploration.

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.

IV. Future Research Directions

RS plays a crucial role in various application fields, supporting the user's decision-making. However, as previously discussed, its effectiveness can be affected by cold-start and data sparsity challenges. As a result, traditional recommendation approaches often struggle to provide accurate and personalised recommendations. This paper analysed the current landscape of RS research, focusing on approaches to address cold-start and data sparsity problems. Based on this analysis, it was possible to identify several promising directions for future research that can have the potential to significantly enhance the performance of the RS and user trust in the system. These research directions include:

- ***Explore the Combination of Enabling Methods:*** The field of RS, initially focused on single-method approaches, is now evolving, proposing a combination of methods through integrating trust, similarity, and AI techniques. The state-of-the-art analysis suggests an emerging trend towards the combination of emerging methods. This creates new opportunities for future research, enabling researchers to identify the most effective pairing of methods depending on the recommendation scenarios. Ultimately, the combination of methods has the potential to improve the accuracy and personalisation of recommendations across different fields.
- ***Develop New Similarity Measures and Methods:*** An essential area of research for mitigating cold-start and data sparsity issues lies in developing new similarity measures. Existing methods often struggle when dealing with users or items with limited data. New approaches are needed to capture user and item similarities effectively, even in cold-start and data sparsity scenarios. By going beyond traditional similarity measures, researchers can generate a more detailed understanding of user-item relationships. This will lead to more accurate recommendations for new users or items with minimal data points. The improvement of similarity measures could be a key to unlocking the full potential of RS, ensuring its function regardless of data limitations.
- ***Exploration of AI-based Algorithms:*** The growing importance of AI-based algorithms in RS is promising, having the potential to overcome limitations imposed by cold-start and data sparsity. Future research should go deeper into AI capabilities, even though these are already used in RS, exploring ways to develop more robust and efficient models. By leveraging AI, researchers can create RS that can make accurate recommendations even with limited user data or for entirely new users. This could significantly improve recommendations' personalisation and user experience.
- ***Explainable Recommendations Systems:*** As user trust and transparency become essential for the optimal function of RS, explainable RS emerge as a future area of research. Traditional RS often function as black boxes, leaving users sceptical of why specific items are recommended. The lack of explanation can interfere with user trust and engagement with the system. To address this, future research should explore techniques that explain the process that led to the recommendations. This is particularly important in cold-start and data sparsity scenarios where limited data makes recommendations less intuitive. By understanding the reasoning behind recommended items, users can make more informed decisions and ultimately feel more confident in the RS.

The performance of RS can be significantly improved by directing efforts towards these future research directions. This enhancement can lead to highly accurate and personalised recommendations and provide better decision support.

V. Conclusion

The emergence of Industry 4.0 technologies like Digital Twins, which leverage RS for decision support and collaboration, has highlighted the critical role of RS. However, even though cold-start and data sparsity are the most common challenges in RS, the ongoing research on these topics demonstrates their continued relevance. This literature review identified the main enabling methods used to mitigate these challenges, such as trust, similarity measures, and AI-based algorithms. With the analysis of the literature, it was possible to identify several research gaps, such as the exploration combinations of different techniques within the identified enabling methods, the development and innovation of new similarity measures combined with AI-based algorithms, the application and exploration of RS in the field of manufacturing and services, the exploration of the possibility of having adaptive approaches, and, in general, there is still space for further exploration regarding the research on mitigating both problems at the same time.

The state-of-the-art analysis has revealed research directions for the future, such as exploring novel combinations of enabling methods, developing new similarity measures, leveraging the power of AI for robust models, creating explainable recommendations, and expanding research beyond established domains. This could potentially improve the overall effectiveness of RS and unlock its full potential within Industry 4.0 applications, empowering decision-makers with a new level of confidence in their recommendations derived from these advanced systems.

Future work will be devoted to mitigating one of the research gaps identified and to further exploring the defined future research directions.

Acknowledgments

This work was supported by national funds through FCT/MCTES (PIDDAC): CeDRI, UIDB/05757/2020 (DOI: 10.54499/UIDB/05757/2020) and UIDP/05757/2020 (DOI:10.54499/UIDP/05757/2020); and SusTEC, LA/P/0007/2020 (DOI:10.54499/LA/P/0007/2020). The author Flavia Pires thanks the FCT Portugal for the PhD Grant SFRH/BD/143243/2019.

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.

REFERENCES

[1] M. Kunath and H. Winkler, "Integrating the digital twin of the manufacturing system into a decision support system for improving the order management process," in *51st CIRP Conf Manuf Syst*, 2018, pp. 225–231.

[2] E. VanDerHorn and S. Mahadevan, "Digital twin: Generalization, characterization and implementation," *Decis Support Syst*, p. 113524, 2021.

[3] M. Bohanec and J. S. Institute, "What is decision support?" in *Proceedings of the 4th International Multi-conference Information Society*, 2001, pp. 86–89. [Online]. Available: https://www.researchgate.net/publication/248421433

[4] T. P. Liang, "Recommendation systems for decision support: An editorial introduction," *Decis Support Syst*, pp. 385–386, 2008.

[5] F. O. Isinkaye, Y. O. Folajimi, and B. A. Ojokoh, "Recommendation systems: Principles, methods and evaluation," *Egypt Inform J*, pp. 261–273, 2015.

[6] S. Malik, A. Rana, and M. Bansal, "A survey of recommendation systems," *Inf Resour Manag J*, pp. 53–73, 2020.

[7] R. Sharma and R. Singh, "Evolution of recommender systems from ancient times to modern era: A survey," *Ind J Sci Technol*, 2016.

[8] F. Pires, P. Leitão, A. P. Moreira, and B. Ahmad, "Reinforcement learning based trustworthy recommendation model for digital twin-driven decision-support in manufacturing systems," *Comput Ind*, 2023.

[9] S. Gupta and M. Dave, *An Overview of Recommendation System: Methods and Techniques.* Springer, 2020, ch. Advances in Computing and Intelligent Systems. Algorithms for Intelligent Systems.

[10] D. Roy and M. Dutta, "A systematic review and research perspective on recommender systems," *J Big Data*, 2022.

[11] S. Chakraborty, S. Hoque, N. R. Jeem, M. C. Biswas, D. Bardhan, and E. Lobaton, "Fashion recommendation systems, models and methods: A review," *Informatics*, pp. 1–34, 2021.

[12] R. Reshma, G. Ambikesh, and P. S. Thilagam, "Alleviating data sparsity and cold start in recommender systems using social behaviour," in *IEEE Int Conf RTIT*, 2016, pp. 1–8.

[13] P. K. Singh, P. K. D. Pramanik, G. Ahuja, A. Nayyar, V. Pandey, and P. Choudhury, "Mitigating sparsity and cold start problem in collaborative filtering using cross-domain similarity," in *8th ICOT*, 2020.

[14] S. Natarajan, S. Vairavasundaram, S. Natarajan, and A. H. Gandomi, "Resolving data sparsity and cold start problem in collaborative filtering recommender system using linked open data," *Expert Syst Appl*, 2020.

[15] K. V. Rodpysh, S. J. Mirabedini, and T. Banirostam, "Resolving cold start and sparse data challenge in recommender systems using multi-level singular value decomposition," *Comput Electr Eng*, 2021.

[16] A. Felsberger, B. Oberegger, and G. Reiner, "A review of decision support systems for manufacturing systems," *CEUR Workshop Proc*, 2017.

[17] L.-T. Weng, "Information enrichment for quality recommender systems," Ph.D. dissertation, Queensland University of Technology, 2008.

[18] J. K. Tarus, Z. Niu, and G. Mustafa, "Knowledge-based recommendation: a review of ontology-based recommender systems for e-learning," *Artif Intell Rev*, pp. 21–48, 2018.

[19] H. Ma, H. Yang, M. R. Lyu, and I. King, "Sorec: Social recommendation using probabilistic matrix factorization," in *17th ACM CIKM*, 2008, pp. 931–940.

[20] J. O'Donovan and B. Smyth, "Trust in recommender systems," in *10th Int Conf IUI*, 2005, pp. 167–174.

[21] A. Selmi, Z. Brahmi, and M. M. Gammoudi, "Trust-based recommender systems: An overview," in *27th IBIMA*, 2016, pp. 371–380.

[22] A. Abdul-Raham and S. Hailes, "Distributed Trust Model," in *Proc NSPW*, 1998, pp. 48–60.

[23] P. Victor, M. De Cock, and C. Cornelis, "Trust and Recommendations." Springer, 2011, ch. Recommender Systems Handbook, pp. 645–675.

[24] Z. Fayyaz, M. Ebrahimian, D. Nawara, A. Ibrahim, and R. Kashef, "Recommendation systems: Algorithms, challenges, metrics, and business opportunities," *Applied Sciences*, p. 7748, 2020.

[25] F. J. Tey, T. Y. Wu, C. L. Lin, and J. L. Chen, "Accuracy improvements for cold-start recommendation problem using indirect relations in social networks," *J. Big Data*, 2021.

[26] E. Çano and M. Morisio, "Hybrid recommender systems: A systematic literature review," *Intell Data Anal*, pp. 1487–1524, 2017.

[27] Y. Xin, "Challenges in recommender systems: Scalability, privacy, and structured recommendations," Ph.D. dissertation, Massachusetts Institute of Technology, 2015.

[28] L. Guo, J. Liang, Y. Zhu, Y. Luo, L. Sun, and X. Zheng, "Collaborative filtering recommendation based on trust and emotion," *J Intell Inf Syst*, pp. 113–135, 2019.

[29] R. K. Sorde and S. N. Deshmukh, "Comparative Study on Approaches of Recommendation Systems," *Int J Comput Appl*, pp. 10–14, 2015.

[30] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, and et al., "The prisma 2020 statement: An updated guideline for reporting systematic reviews," *International Journal of Surgery*, vol. 88, 2021.

[31] P. Massa and P. Avesani, "Trust-aware Recommender Systems," in *ACM RecSys*, 2007, pp. 17–24.

[32] H. J. Ahn, "A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem," *Inf Sci*, pp. 37–51, 2008.

[33] Y. Koren, "Factorization meets the neighborhood: a multifaceted collaborative filtering model," in *14th ACM SIGKDD*, 2008, pp. 426–434.

[34] M. Jamali and M. Ester, "TrustWalker: A random walk model for combining trust-based and item-based recommendation," in *15th ACM SIGKDD*, 2009, pp. 397–405.

[35] H. Ma, I. King, and M. R. Lyu, "Learning to recommend with social trust ensemble," in *32nd ACM SIGIR*, 2009, pp. 203–210.

[36] M. Jamali and M. Ester, "A matrix factorization technique with trust propagation for recommendation in social networks," in *4th ACM RecSys*, 2010, pp. 135–142.

[37] H. Ma, D. Zhou, C. Liu, M. R. Lyu, and I. King, "Recommender systems with social regularization," in *4th ACM WSDM*, 2011, pp. 287–296.

[38] W. Y. Zhang, S. Zhang, Y. G. Chen, and X. W. Pan, "Combining social network and collaborative filtering for personalised manufacturing service recommendation," *Int J Prod Res*, pp. 6702–6719, 2013.

[39] U. Marung, N. Theera-Umpon, and S. Auephanwiriyakul, "Applying memetic algorithm-based clustering to recommender system with high sparsity problem," *J Cent South Univ*, pp. 3541–3550, 2014.

[40] G. Guo, J. Zhang, and D. Thalmann, "Merging trust in collaborative filtering to alleviate data sparsity and cold start," *Knowl Based Syst*, pp. 57–68, 2014.

[41] H. Liu, Z. Hu, A. Mian, H. Tian, and X. Zhu, "A new user similarity model to improve the accuracy of collaborative filtering," *Knowl Based Syst*, pp. 156–166, 2014.

[42] G. Guo, J. Zhang, and N. Yorke-Smith, "Trustsvd: Collaborative filtering with both the explicit and implicit influence of user trust and of item ratings," in *Proc AAAI*, 2015, pp. 123–129.

[43] X. Zhang, J. Cheng, S. Qiu, G. Zhu, and H. Lu, "Dualds: A dual discriminative rating elicitation framework for cold start recommendation," *Knowl Based Syst*, pp. 161–172, 2015.

[44] P. Moradi, S. Ahmadian, and F. Akhlaghian, "An effective trust-based recommendation method using a novel graph clustering algorithm," *Physica A*, vol. 436, pp. 462–481, 2015.

[45] I. Barjasteh, R. Forsati, D. Ross, A. H. Esfahanian, and H. Radha, "Cold-start recommendation with provable guarantees: A decoupled approach," *IEEE Trans Knowl Data Eng*, pp. 1462–1474, 2016.

[46] B. Yang, Y. Lei, J. Liu, and W. Li, "Social collaborative filtering by trust," *IEEE Trans Pattern Anal Mach Intell*, pp. 1633–1647, 2017.

[47] M. Sun, F. Li, and J. Zhang, "A multi-modality deep network for cold-start recommendation," *Big Data and Cognitive Computing*, pp. 1–15, 2018.

[48] M. H. Mohamed, M. Khafagy, and H. Elbeh, "Sparsity and cold start recommendation system challenges solved by hybrid feedback," *Int J Eng Res Technol*, vol. 12, pp. 2734–2741, 2019.

[49] R. A. Rupasingha and I. Paik, "Alleviating sparsity by specificity-aware ontology-based clustering for improving web service recommendation," *IEEJ Trans Electr*, vol. 14, pp. 1507–1517, 2019.

[50] Z. Zhang, Y. Zhang, and Y. Ren, "Employing neighborhood reduction for alleviating sparsity and cold start problems in user-based collaborative filtering," *Inf Retr J*, pp. 449–472, 2020.

[51] V. K. Sejwal and M. Abulaish, "A hybrid recommendation technique using topic embedding for rating prediction and to handle cold-start problem," *Expert Syst Appl*, 2022.

[52] A. Panteli and B. Boutsinas, "Addressing the cold-start problem in recommender systems based on frequent patterns," *Algorithms*, 2023.

[53] K. V. Rodpysh, S. J. Mirabedini, and T. Banirostam, "Employing singular value decomposition and similarity criteria for alleviating cold start and sparse data in context-aware recommender systems," *Electron Commer Res*, pp. 681–707, 2023.

Authorized licensed use limited to: b-on: Instituto Politecnico de Braganca. Downloaded on December 13,2024 at 16:23:15 UTC from IEEE Xplore. Restrictions apply.