A challenge-based survey of e-recruitment recommendation systems

YOOSOF MASHAYEKHI, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Belgium

NAN LI, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Belgium

BO KANG, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Belgium

JEFREY LIJFFIJT, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Belgium

TIJL DE BIE, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Belgium

E-recruitment recommendation systems recommend jobs to job seekers and job seekers to recruiters. The recommendations are generated based on the suitability of job seekers for positions and on job seekers' and recruiters' preferences. Therefore, e-recruitment recommendation systems may greatly impact people's careers. Moreover, by affecting the hiring processes of the companies, e-recruitment recommendation systems play an important role in shaping the competitive edge of companies. Hence, it seems prudent to consider what (unique) challenges there are for recommendation systems in e-recruitment. Existing surveys on this topic discuss past studies from the algorithmic perspective, e.g., by categorizing them into collaborative filtering, content-based, and hybrid methods. This survey, instead, takes a complementary, challenge-based approach. We believe this is more practical for developers facing a concrete e-recruitment design task with a specific set of challenges, and also for researchers that look for impactful research projects in this domain. In this survey, we first identify the main challenges in the e-recruitment recommendation research. Next, we discuss how those challenges have been studied in the literature. Finally, we provide future research directions that we consider most promising in the e-recruitment recommendation domain.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Information systems → Recommender systems**.

Additional Key Words and Phrases: Job recommendation, E-recruitment recommendation

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1 INTRODUCTION

Recommendation systems have significantly impacted various domains by helping users find suitable content, from healthcare [140, 161] and education [62] to scholarly activities [100]. Among these, the domain of e-recruitment has emerged as a critical area of application [58]. With the ever-increasing use of the world wide web, many people now

Authors' addresses: Yoosof Mashayekhi, yoosof.mashayekhi@ugent.be, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Ghent, Belgium, 9000; Nan Li, nan.li@ugent.be, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Gent, Belgium, 9000; Bo Kang, bo.kang@ugent.be, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Gent, Belgium, 9000; Jefrey Lijffijt, jefrey.lijffijt@ugent.be, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Gent, Belgium, 9000; Tijl De Bie, tijl.debie@ugent.be, IDLAB - Department of Electronics and Information Systems (ELIS), Ghent University, Gent, Belgium, 9000.

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seek jobs on e-recruitment platforms, such as LinkedIn[1], which assist job seekers in applying to various positions and enable recruiters to find suitable candidates for their job openings [64, 89, 124].

This focus on e-recruitment within the broader spectrum of recommendation systems underscores its importance. E-recruitment recommendation systems impact the career opportunities of job seekers in several aspects. Since usually there are a large number of vacancies available on e-recruitment platforms, job seekers are typically not aware of all opportunities that are relevant to them. Hence, recommendation systems play an important role in helping job seekers find suitable vacancies. Moreover, recommendation systems also impact their chance of employment by recommending the same vacancies to other job seekers, which may result in increased or decreased competition for those positions. Hence, effective matching in e-recruitment can significantly enhance the hiring process's efficiency, positively affecting job seekers' career paths. Moreover, getting the best recommendations of suitable candidates for recruiters gives companies a competitive edge in the job market, by strengthening the hiring process and securing top talent swiftly and efficiently. Conversely, poor matches between job seekers and vacancies can waste time and effort for both parties and potentially have a negative impact on the labor market, corporate competitiveness, and individuals' long-term livelihoods. Therefore, due to its unique properties and the profound impact it can have, the domain of recommendation in e-recruitment deserves specific attention.

In this study, we review the literature of the past decade about e-recruitment recommendation systems. Existing surveys on e-recruitment recommendation systems [41, 58] focused on categorizing papers based on their methods, such as collaborative filtering, content-based, hybrid, etc. However, studies typically try to address specific challenges of the recommendation task in e-recruitment systems, i.e., specific problems in recommendation such as scalability. The range of challenges that all these different methods address has not been categorized in these prior surveys. Therefore, in this survey, we focus on the challenges for e-recruitment recommendation systems and how those challenges have been studied in the literature.

Our motivation to use the concept of a challenge-based approach in this survey is that we believe it is useful both for developers of e-recruitment recommendation systems and for researchers in the field. Developers will typically look for solutions to the practical challenges that naturally pose themselves in the design of their e-recruitment recommendation system. For example, reviewing the solutions to scalability surveyed in this paper assists developers in addressing scalability issues in real-time recommendation. For researchers, our challenge-based approach may help in identifying the most impactful research problems of the domain and proposed solution approaches to address them that have already been attempted. Moreover, open challenges and future research directions are also discussed, to provide guidance for future research in this domain.

There exist challenges from different perspectives in e-recruitment recommendation systems. The challenges discussed in the survey are primarily technical. The objective of this survey is to assist developers and researchers working on technical aspects of e-recruitment recommendation systems and provide them with practical insights.

Terminology. Different entities could be recommended in e-recruitment recommendation systems. The e-recruitment recommendation systems could be categorized into three groups based on the **entities being recommended**: *job recommendation*, *job seeker recommendation*, and *reciprocal recommendation*. In the rest of the paper, we use the term **e-recruitment recommendation** to refer to all recommendation systems in this research area.

Unless otherwise stated, the terms **user** and **item** refer to job seekers, job positions, or recruiters, depending on the context: users receive the recommended lists, and items are the entities recommended to users. Throughout this paper,

[1] https://www.linkedin.com/

the terms job, job posting, job position, vacancy, and opening are used interchangeably to refer to a job vacancy. The terms recruiter or employer are also used interchangeably to refer to the person responsible for a job position. CVs and resumes denote the textual content of job seekers. We refer to all features and textual content of the users (job seekers or job postings) by the term user profile. Since different terms are used for the job/job seeker recommendation in the literature, we also use phrases such as matching job seekers with job positions (e.g., [94, 173]), person-job fit (e.g., [95, 129]), and recommendation in e-recruitment (e.g., [35, 57]) to denote the same concept of recommendation in e-recruitment.

Contributions. This survey will provide an overview of the literature in the past decade (from 2012 onwards) on e-recruitment recommendation systems. It contains the following contributions:

- Underscoring the importance of a survey on this topic, we list and discuss some important specific characteristics of e-recruitment recommendation systems that make it clear why they require a dedicated approach.
- We identify and briefly discuss eight challenges that were frequently addressed by research papers covered in this survey, and where appropriate explain how they are the result of specific characteristics of e-recruitment recommendation systems.
- For each of these challenges, we discuss the papers that have specifically targeted it, and we briefly discuss their approaches.
- We provide future research directions and discuss the challenges that have been investigated less in recent years.
- We present a structured overview of the collected 123 papers in Table 1 in the Appendix. The available properties of each paper in Table 1 are the recommendation type based on the recommended entities (job, job seeker, reciprocal), recommendation method type, and the challenges that the paper has addressed.
- We maintain a website[2] containing the content of Table 1 along with paper metadata (e.g. venue, URL, authors, etc.) and summaries of the selected papers. We hope this can further facilitate future research in e-recruitment recommendation systems.

For the remainder of this section, we first discuss more in detail how our survey complements the existing surveys (Section 1.1). Next, we describe how the papers were collected and filtered (Section 1.2). Finally, we discuss the structure of this survey (Section 1.3).

1.1 Differences with previous recent surveys

The two recent surveys on e-recruitment recommendation systems [41, 58] organized the literature differently from the present survey. The work by Freire and de Castro [58] focused on method types, data sources, and assessment methods. The work by de Ruijt and Bhulai [41] gave an in-depth discussion about the e-recruitment recommendation system methods with a focus on categorizing hybrid and ensemble hybrid methods. Although de Ruijt and Bhulai [41] explored some challenges of e-recruitment recommendation systems such as scalability, ethical, and reciprocal aspects, their discussion on those challenges and aspects is brief and limited.

Since the type of recommendation methods is well discussed in previous papers, this aspect is not the focus of the present study. Given the limitations of previous surveys, we focus on the specific problems and challenges in e-recruitment recommendation systems and discuss the solutions that have been proposed for those challenges from a technical point of view. Our survey is valuable in that we emphasize the distinguishing nature of e-recruitment and organize the literature with respect to the special difficulties and challenges in e-recruitment recommendation.

[2]https://aida-ugent.github.io/e-recruitment-recsys-challenges/

1.2 Literature search methodology

We crawled data from dblp[3] using ten keywords: {'job recommender', 'job recommendation', 'job matching', 'e-recruitment', 'e-recruiting', 'online recruitment', 'person-job fit', 'vacancy recommendation', 'candidate recommendation', 'occupation recommendation'} and as a result, 543 papers were collected. We selected all papers published since (including) 2012 that have at least five citations and all papers published since (including) 2020. Papers that are not about the recommendation of jobs or job seekers were removed since they are out of the scope of this survey. For example, papers that recommend a general career to the user are excluded. This approach resulted in 126 papers in total. We further collected 27 papers from industry leaders and known experts from top conferences and journals. In total, 153 papers were kept for further examination.

1.3 Structure of the survey

The remainder of the survey is structured as follows. In Section 2, we discuss the properties that distinguish e-recruitment recommendation systems from other recommendation systems. Section 3 contains our findings, in which Section 3.1 gives a bird's eye view of all the challenges identified in this survey, Section 3.2 to 3.9 addresses the different challenges respectively, and Section 3.11 briefly talks about the remaining papers not covered in the challenge sections. Finally, Section 4 concludes our findings and discusses the limitations of this survey, open challenges and future directions.

2 SPECIFIC CHARACTERISTICS AND PROPERTIES OF E-RECRUITMENT RECOMMENDATION SYSTEMS

In this section, we discuss the differences between e-recruitment and traditional recommendation systems. Although many challenges and characteristics are common between an e-recruitment recommendation system and a traditional one, such as e-commerce or a movie recommender, certain aspects set e-recruitment recommendation systems apart:

(1) **One worker, one job (OWOJ)**: At a certain period of time, a person can only work at one or a few jobs, and also companies hire one or a few employees for a job posting [26]. Moreover, job seekers and job positions are mostly available for a limited time and become inactive after they are employed or filled. In contrast, in a traditional recommender, the same items can be recommended to many users, and users consume several items. The e-recruitment recommendation systems have to consider this aspect in the recommendation. First, the number of recommendations for each job/job seeker may have to be kept relatively small since only one or a few of them can succeed. Moreover, job seekers/jobs usually compete with each other for the same jobs/job seekers. Hence, the recommendation of a job at which others have a higher chance of success could be less interesting. This competition aspect should ideally be taken into consideration in generating the recommendations.

(2) **Two-sided engagement (TSE)**: E-recruitment systems inherently involve multiple stakeholders, notably job seekers, and employers, a characteristic shared with other recommendation domains. However, unlike traditional recommendation systems where success is often gauged by unilateral user actions (e.g., a viewer selecting a movie to watch on a streaming platform), e-recruitment recommendations necessitate reciprocal actions for success. In domains such as movie or music recommendations, the engagement and satisfaction metrics are predominantly user-centric, focusing on individual preferences and interactions. Conversely, e-recruitment systems operate within a distinctly two-sided framework, where the efficacy of a recommendation is contingent upon mutual engagement: a job seeker's application is merely the initial step, requiring a corresponding acceptance or offer from the employer to culminate successfully. This dual-dependency model underscores the unique challenge of

[3]https://dblp.org/

aligning interests and actions across both job seekers and employers, necessitating a more nuanced approach to recommendation strategies that can effectively bridge this bidirectional engagement gap.

(3) **Suitability as well as preference (SP)**: While users' preferences play an important role in all recommendation systems, e-recruitment recommendation systems recommend jobs/job seekers based on suitability and skills as well [71]. One way to define suitability and user preference is as follows. *Suitability* represents the degree of matchness between a job seeker and job position based on typically but not exclusively knowledge, skills, diplomas, and years of experience of the job seekers and the job position requirements. User *preference*, on the other hand, represents one's inclination towards certain items. For example, a job seeker might be suitable for several positions but prefer to work for a specific company for various reasons such as higher salary, social connections, etc. In addition, a recruiter often has to pick one job seeker among multiple equally suitable job seekers based on preferences such as social connections, personality, etc. Hence, the suitability of a job seeker for a job and their preferences will in general not be equal, which poses specific challenges to e-recruitment recommendation systems.

(4) **Multi-faceted (MF)**: In e-recruitment recommendation systems, both suitability and preference are, in fact, dependent on many different facets with different data types. For a job seeker, their previous job history, diplomas, seniority, interests, skills, location, social fit to the job environment, etc. could be relevant for an e-recruitment recommendation system. For a job posting, its required skills, required diplomas, seniority, location, organizational culture, etc. might be available and could be used in an e-recruitment recommendation system. Hence, the nature of data available in the e-recruitment domain is usually multi-faceted and requires specific attention in designing e-recruitment recommendation systems.

(5) **High-stakes (HS)**: E-recruitment is a high-risk domain because it can have a long-term impact on people's careers and hence, their career fulfillment. Moreover, it plays an important role in shaping the companies' competitive edge in the market. E-recruitment is even defined as one of the high-risk domains according to the EU's AI act (proposal) [38]. Hence, considering fairness and trustworthiness aspects is more essential in e-recruitment recommendation systems compared to the traditional ones.

(6) **Short interaction history (SIH)**: The e-recruitment domain is characterized by its inherently transient job listings and job seeking patterns, resulting in insufficient interaction data. Unlike movies or music tracks that remain available for an extended period, job positions frequently emerge and are promptly removed from the market once filled. This rapid turnover poses significant challenges for recommendation systems, as the window for collecting user interactions with any given job listing is exceedingly narrow [69]. Furthermore, the episodic engagement of job seekers with the system—typically ceasing once employment is secured—compounds the difficulty of accumulating a rich interaction history. Hence, most of the interaction data available for the training corresponds to the jobs and job seekers that are not active in the system anymore. Although the recommendation models can still learn some patterns using that data for the active entities (job seekers and job positions) in the system, learning effective patterns for active entities compared to other domains such as music or movie recommendation is more challenging due to their short interaction history.

3 SURVEY STRUCTURED ACCORDING TO CHALLENGES FACED IN THE DEVELOPMENT OF E-RECRUITMENT RECOMMENDATION SYSTEMS

In this survey, we identify some challenges in e-recruitment recommendation systems that have been addressed by studies in recent years. Although there would be many other challenges in the e-recruitment recommendation domain, we focus on the most common ones here.

We first list the main challenges in e-recruitment recommendation systems and describe each of the challenges in Section 3.1. Next, we introduce the methods that have been proposed to deal with each of the challenges in Sections 3.2 to 3.9. Then, in Section 3.10, we briefly discuss several trends and patterns that we observed in the existing literature. Finally, we discuss the papers that are not included in the sections covering challenges (Section 3.11). Moreover, in each section, we provide a visual overview of the problems and solutions (Fig. 1 to Fig. 8). They contain the solutions that we **observed** in the literature. Of course, other solutions that have not yet been described in the literature may exist.

3.1 A preview of the challenges

1) **Data quality**: E-recruitment recommendation systems often have a plethora of data sources, including interactions and textual data from job seekers (CVs) and job postings (job descriptions). There are many relevant facets in the available data (MF aspect 2.4), but with variable quality. Moreover, some facets, e.g. skills, might be implicit and need to be extracted from unstructured data. Some common issues in dealing with such data are:
   a. **Data cleaning and preprocessing**. Recommendation systems usually use features extracted from textual data, which is usually noisy. Hence, data cleaning preprocessing is necessary and crucial for better feature extraction and downstream tasks.
   b. **Semantic gap**. The textual data is usually written by different people, and different terms are often used to address the same concept. This semantic gap results in poor semantic matching.
   c. **Skill extraction**. Although many facets might be implicit and need to be extracted with carefully designed methods, we focus on skills, which are the most important feature in matching job seekers with job postings. Using job seekers' skills and the job postings' required skills is necessary for increasing the performance of e-recruitment recommendation systems. Hence, skill extraction from the textual data is another challenging task in the e-recruitment recommendation systems.
   d. **Multi-linguality**. In some countries/platforms, job seekers' resumes and job descriptions are written in several languages. In such cases, e-recruitment recommendation systems should support multiple languages for the textual content.
   e. **Data sparsity**. Many recommendation systems suffer from data sparsity issues, e-recruitment recommendation is no exception (SIH aspect 2.6). The reason is that job seekers may only use the system a few times and then leave the platform forever after a successful job-hunting; the same is true for vacant job positions: new jobs might appear on a daily basis but disappear quickly after receiving satisfying applications.
2) **Heterogeneous data, and multiple interaction types and data sources**: E-recruitment recommendation systems could use more data sources compared to many other kinds of recommendation systems, as they might have access to job seekers' previous work experiences, interviews, the textual content of their resumes/job descriptions, skills, and preferences (MF aspect 2.4). The availability of unstructured, semi-structured and structured data makes e-recruitment recommendation systems have to deal with the heterogeneous nature of data.

In addition, there are also many interaction types in the recommendation systems between job seekers and job postings, e.g., view, click, apply, chat, favorite, like, and comment. Using different interaction types between job seekers and job postings could be both a challenge and an opportunity in the development of e-recruitment recommendation systems.

Moreover, recommendation systems could also make use of other data sources besides job market-related data, such as job seekers' and job postings' information in social networks, blogs, etc.

3) **Cold start**: The cold start problem in recommendation systems refers to the problem of recommending to new users or recommending new items with few or no interactions. This problem might be more acute for e-recruitment recommendation systems than the traditional ones since new jobs tend to appear and disappear frequently (SIH aspect 2.6). The jobs usually disappear after a successful match, and new jobs with the same title are often posted as new items. In contrast, the products with the same name in traditional recommenders are usually treated as the same item, and only their availability changes over time (in cases such as movie recommenders, the product is always available).

   Using data other than interactions could often alleviate the cold start problem in recommendation systems. Hence, it is helpful to have the many facets available in the job seekers' and job postings' profiles (MF aspect 2.4). Also note that in e-recruitment recommendation systems terms, there are user (job seeker or job) cold start and item (job or job seeker) cold start problems. In job recommendation, user cold start refers to job seeker cold start and item cold start refers to job cold start, and it is the other way around in job seeker recommendation.
4) **User preferences as well as suitability**: To find the best matches between job seekers and vacancies, it is crucial to use the knowledge and skills of the job seekers and the requirements of job positions. However, users' preferences are equally important for a personalized recommendation system (SP aspect 2.3).
5) **Interpretability and explainability**: Providing explainable recommendations and designing interpretable models are important in e-recruitment recommendation systems (HS aspect 2.5). Job seekers could benefit from explanations of their recommendations since important career decisions will depend on their choices. Moreover, providing explainable results helps design user-friendly applications for job-seekers and recruiters.
6) **Specific objectives**: E-recruitment recommendation systems usually have a multi-objective nature, since they need to satisfy multiple stakeholders, including job seekers, recruiters, and service providers (TSE aspect 2.2). In addition, e-recruitment recommendation systems could have specific objectives, such as balancing the number of recommendations each job seeker/job posting receives or recommending items with a high chance of success regarding the competitors (OWOJ aspect 2.1), or avoiding false positives to make sure that users wouldn't be bothered by too many spams.
7) **Bias and fairness**: Recommendation systems suffer from all kinds of well-known biases, some of which have raised societal and ethical concerns. Providing fair recommendations in e-recruitment is even more essential than the other types since e-recruitment is a high-stakes domain (HS aspect 2.5). It is crucial to mitigate biases for job seekers, such as gender bias, as well as biases regarding job postings, such as recency bias (recent job postings may be more popular).
8) **Scalability**: The ever-increasing amounts of data bring the pressing challenge of scalability to the e-recruitment recommendation systems. More specifically, large-scale data may cause issues in both training and inference phases: in each phase, there could be issues with speed and storage/memory consumption.

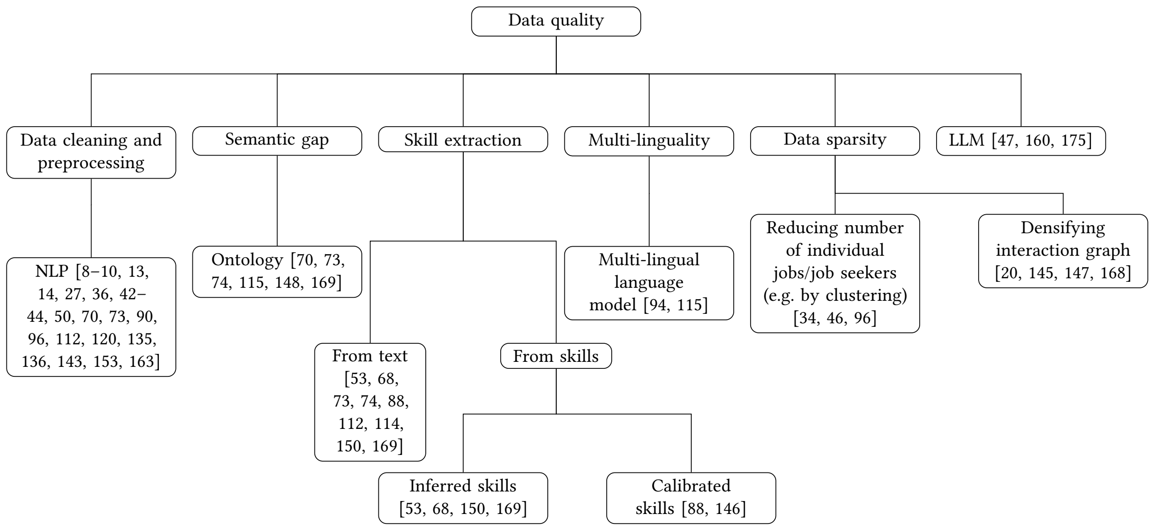

Fig. 1. An overview of the *data quality* challenge

3.2 Data quality

Since most e-recruitment recommendation systems use interactions as well as textual data (resumes and job descriptions) to model the user profile or to construct features, various data quality issues affect the quality of recommendations. Most issues in this section are about textual data quality since the facets available in e-recruitment (MF aspect 2.4) are sometimes hidden in free text. We briefly discuss different approaches for each data quality issue discussed in Section 3.1.1. Moreover, we briefly discuss the use of Large language models to increase the data quality in general and help the recommendation task. An overview of this section which includes the categories of the data quality issues and the corresponding solutions in the literature, is presented in Fig. 1.

Data cleaning and preprocessing (Section 3.1.1.a). E-recruitment recommendation systems usually use textual content to acquire features for job seekers and job descriptions, which could further be used in recommendation methods. However, the textual contents are usually written by different people and are noisy. Therefore, data cleaning and data preprocessing for textual data are crucial for providing high quality recommendations.

Although most approaches using textual content have to do some data cleaning and preprocessing, we only discuss the works that have explicitly focused on NLP techniques to deal with such issues. The data cleaning and preprocessing usually involve common NLP techniques such as tokenization, removing stop words, stemming, and lemmatization [8–10, 13, 14, 27, 36, 42–44, 50, 70, 73, 90, 96, 112, 120, 135, 136, 143, 153, 163].

Semantic gap (Section 3.1.1.b). Since the textual data is written by different people, e-recruitment recommendation systems suffer from a semantic gap between contents from different sources, such as resumes and job descriptions. Different terms might have been used to refer to the same concept. Moreover, the same term could have different meanings depending on the context.

Although most papers that use language models or learn representations of textual data can alleviate the semantic gap to some degree, we only discuss the papers that explicitly focus on this issue. The most common approach that is employed in the literature to tackle the semantic gap is to map skills/concepts to the nodes in an ontology (by exploiting a language model, using Named Entity Recognition (NER), Named Entity Disambiguation (NED), etc.) and to use the shared nodes to refer to the same skills/concepts [70, 73, 74, 115, 148, 169].

Skill extraction (Section 3.1.1.c). E-recruitment recommendation systems mostly match job seekers with job postings based on their expertise and skills. Since job seekers' profiles and job descriptions are often available as free text with no structure, skill extraction from the textual data is important for some e-recruitment recommendation systems. Some papers have employed NLP techniques such as n-gram tokenization [112], NER [68, 74, 88, 112, 114], part-of-speech tagging (PoS tagging) [68], using skill dictionaries or ontology [53, 68, 73, 74, 88, 112, 169], or other techniques (e.g., using the context of a skill term, called skill headwords) [150] to extract skills from the text. Job seekers' and job postings' skills have also been expanded using skill similarities or relations provided by word embedding models (e.g., word2vec) [68, 150], training model based on an existing skill dictionary [169], and by domain specific ontologies or skill taxonomies [53]. On the other hand, some studies develop techniques to calibrate the extracted skills [88, 146]. Given the extracted skills for job seekers and job postings by an in-house skill tagger in LinkedIn, Shi et al. [146] selected skills for job postings considering the market supply (enough job seekers having that skill) of the skills and also the importance of each skill in a job posting.

Multi-linguality (Section 3.1.1.d). Some e-recruitment recommendation systems are multi-lingual, i.e., the textual content of resumes and job descriptions could be in multiple languages. Moreover, matching resumes and job descriptions with different languages results in cross-linguality challenges. Such issues have been studied in [94, 115], where a multi-lingual language model was used to support multiple languages. Lavi et al. [94] designed a Siamese architecture to fine-tune the multi-lingual Bert using the historical data of recruiters' interactions with candidates.

Data sparsity (Section 3.1.1.e). E-recruitment recommendation systems often suffer from data sparsity issues (SIH aspect 2.6) due to the fact that similar job positions are usually considered as separate entities. Moreover, job seekers often stop using the platform after being employed. Although most approaches that use content in the recommendation could alleviate the data sparsity issue to some extent (e.g. [15]), we only discuss the works that study data sparsity explicitly.

One approach that has been studied to cope with the data sparsity issue is to reduce the number of distinct job positions by splitting a job position into a job title and a company name [96] or by clustering similar job positions [34, 46]. Another approach designed by Shalaby et al. [145] is to densify the graph of jobs, which is created based on interactions, by adding content similarity links between the entities (job seekers and job positions). The recommendations are then generated using this graph of jobs. In another approach, Bied et al. [20] used an application interaction graph besides a hire interaction graph to reduce data sparsity. Yang et al. [168] also designed a multi-task from several interaction types where they share text and graph embedding to alleviate the data sparsity problem. Shi et al. [147] tackled the data sparsity problem by designing a multi-objective person-job fit matching model that uses multiple interaction types.

LLM. Large language models have recently been widely used for many tasks in AI, including recommendation systems. They can help with increasing the quality of data available in free-text in e-recruitment and improve the performance of the recommendation task.

Two approaches have been studied in the papers discussed in this survey to use LLM in e-recruitment recommendation. The first approach is to generate higher quality data using an LLM. In [47], an LLM is used to generate a higher quality resume, while in [175], a job description is generated for a resume by an LLM to be used as an auxiliary feature for the recommendation task. The second approach to using LLMs in e-recruitment recommendation is using them as the recommendation engine. Wu et al. [160] fine-tune an LLM by constructing meta-paths from behavioral data to enhance the recommendation by an LLM.

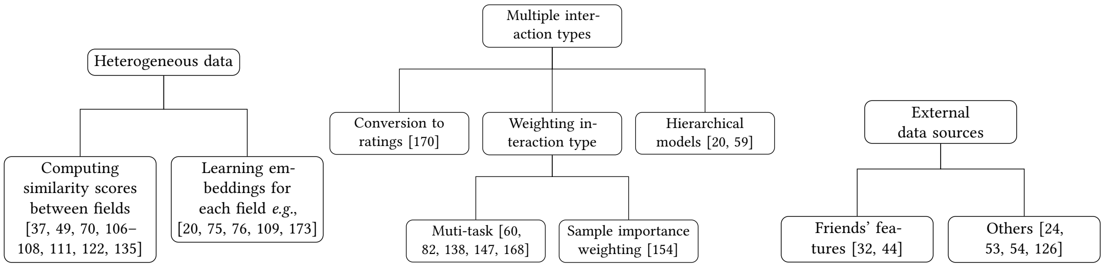

Fig. 2. An overview of the *heterogeneous data, and multiple interaction types and data sources* challenge

3.3 Heterogeneous data, and multiple interaction types and data sources

E-recruitment recommendation systems could use the heterogeneous data of job seekers and job postings, including location, textual resume/job description, skills, etc. (MF aspect 2.4). Moreover, different types of behavioral data are available, where using such data is challenging in recommendation systems. In addition, job seekers' and job positions' data could be enriched by their information from external sources. We briefly discuss the papers dealing with these three aspects that are also described in Section 3.1.2. An overview of this section is presented in Fig. 2.

Since resumes and job descriptions are among the most important data sources for e-recruitment, it is necessary to carefully use them as well as behavioral data. Job seeker profiles, resumes, and job descriptions sometimes have several fields with different data types. Hence, the **heterogeneous nature of the data** should be considered in designing recommendation systems in e-recruitment.

Many papers use features with different types in a recommendation algorithm (e.g., decision trees, deep neural networks, knowledge graphs, etc.) either directly or by some feature representation techniques such as one-hot encoding, word embedding, etc. (e.g., [66, 129]). However, some methods are explicitly designed to work with heterogeneous data. Hence, we focus on those papers for this challenge. Some studies have combined the similarity scores between the same fields (e.g., education, work experience, etc.) of resumes and job postings [37, 49, 70, 106–108, 122, 135] or between all fields in resumes and job postings [111]. Learning embeddings for each of the fields/data sources of job seeker profiles and job postings, and using the interactions of those embeddings to match job seekers with job postings is another approach employed to deal with heterogeneous data [20, 75, 76, 109, 173]. More specifically, Zhao et al. [173] provided recommendations based on the fused embeddings of job seekers and jobs, where they combine the embeddings learned from the textual content, job-skill information graph, and geolocation data. In the deep neural networks proposed in [75, 76], the embeddings for the same fields/field types of resumes and job postings were learned by their inner interactions. In [75], a multi-head self-attention module was then applied to the embeddings for different fields as the field outer interaction module. In [109], different embeddings are learned for different fields of job seekers by their interactions in the neural network. Finally, the learned embeddings were passed to a multi-layer perceptron to compute the matching score between a resume and a job posting [75, 76, 109].

Moreover, there could be **multiple types of interactions** between a job seeker and a job position, such as click, apply, like, favorite, invite, interview, hire, etc., where some of them are initiated by the job seeker and some by recruiters. Zhang and Cheng [170] transformed the implicit feedback (click, bookmark, reply, and click) into ratings and proposed a two-stage ensemble method for generating the recommendations. In another approach, some studies design a multi-task objective to learn from multiple interaction types [60, 82, 138, 147, 168]. Volkovs et al. [154] proposed a

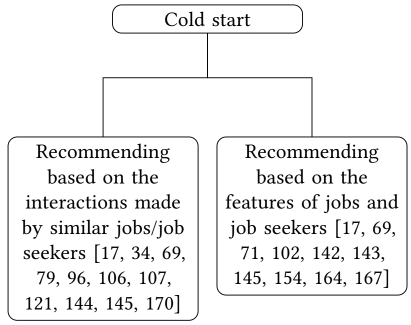

Fig. 3. An overview of the *cold start* challenge

content-based recommendation system considering different interaction types as positive with different weights for sampling and used XGBoost to optimize the binary classification loss. In another approach, some studies [20, 59] used the prediction model of job seeker or job position interactions (such as apply or review) as the input to the model for predicting the overall hire probability.

To find a better match between job seekers and vacancies, information other than skills such as personality and traits has also been found to be useful. Some studies have tried to use auxiliary information gathered from **external data sources** such as friends' features in social networks [32, 44] and personal websites or social media posts [24, 53, 54, 126] to build more comprehensive profiles and improve the recommendations.

3.4 Cold start

As discussed in Section 3.1.3, cold start in recommendation systems refers to the problem of recommending to new users or items with no or few interaction data. This problem could be more acute for e-recruitment recommendation systems because job opening positions are usually treated as distinct items even if they have the same job title and description, and hence those job openings would be treated as new items (SIH aspect 2.6). E-recruitment recommenders could suffer from both job seeker cold start and job cold start problems.

Using content to provide recommendations could alleviate the cold start problem. In the e-recruitment domain, many facets are often available for this purpose (MF aspect 2.4). Hence, papers with content-based approaches or methods that use features based on the content could deal with the cold start problem to some extent. However, we only discuss the papers that explicitly address the cold start problem. The papers dealing with cold start follow two general approaches: recommending using the interactions made by similar jobs/job seekers or predicting the recommendation score based on job seekers' and jobs' features. Some papers also employ both approaches to deal with the cold start problem. An overview of this section, including the solutions proposed by recent studies for the cold start problem, is presented in Fig. 3.

Two approaches have been used in the literature that recommend based on the **interactions made by similar jobs/job seekers**. First, to compute the matching scores between jobs and new job seekers, some studies find similar job seekers to the new ones based on content features and then use the known (e.g., previously interacted) matching scores between them and the jobs [34, 79, 106, 107, 121]. In papers [106, 107], jobs are recommended to new graduate students based on the job offers of similar graduates. In another study by Chen et al. [34], a context-aware multi-arm bandit was employed for generating job recommendations, where the job recommendation scores for new job seekers were

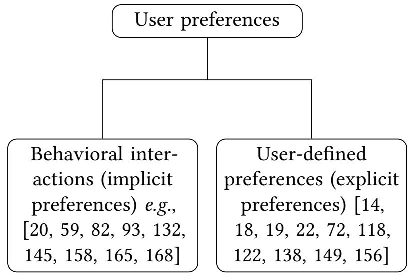

Fig. 4. An overview of the *user preferences as well as suitability* challenge

computed based on the interaction history of similar job seekers. This method could also deal with the job cold start in case of job seeker recommendation due to the symmetric nature of their model architecture. Second, to compute the matching scores between new jobs and job seekers, some studies find jobs with similar content to the new ones and use the known (e.g., previously interacted) matching scores between them and the job seekers [17, 69, 96, 121, 144, 145, 170].

In another approach, some studies **predict the matching scores between job seekers and jobs using their features** to deal with the cold start problem (e.g., using a machine learning method or a scoring function). The job categories that new job seekers are interested in are predicted using job seekers' textual content [145] or attributes [71] and are further exploited to provide job recommendations. Other papers have provided recommendations based on job seekers' and jobs' content, which tackle both job seeker cold start ad job cold start problems [17, 142, 143, 164, 167] (Although many content-based methods could tackle the cold start problem with the same approach, here we only cite the papers that have explicitly addressed the cold start problem). Besides features extracted from job seekers' and jobs' content, several studies [69, 102, 142, 154] also extracted features for job seekers based on the jobs they have interacted with before. Hence, they can deal with the job cold start problem.

3.5 User preferences as well as suitability

Although considering user preferences is important in all recommendation systems, e-recruitment recommendation systems should also consider suitability in generating the recommendations, i.e. matching job seekers with job postings based on the similarity of their skills and requirements (SP aspect 2.3). Since matching based on the suitability of job seekers for job positions has been the main focus of e-recruitment recommendation systems, we discuss the studies focusing on capturing user preference. Suitability is usually captured by matching the requirements of a job position with the skills and other features of the job seekers, while preference is often captured by other factors in the profiles of job seekers and job postings, such as location, interests, etc., or by behavioral interactions. In this section, we discuss the methods explicitly modeling user preferences either based on explicit preferences in user profiles or using a preference model. An overview of this section is presented in Fig. 4.

Behavioral interactions between job seekers and job postings, such as click, apply, invite, etc., can show the user preferences to some extent. Hence, E-recruitment recommendation systems that use such behavioral interactions in their method are considering user preferences in generating recommendations (e.g., [71, 93, 132, 145, 158, 165]). Moreover, some studies use interactions initiated by both job seekers and job postings to learn the preferences of both sides [20, 59, 82, 168].

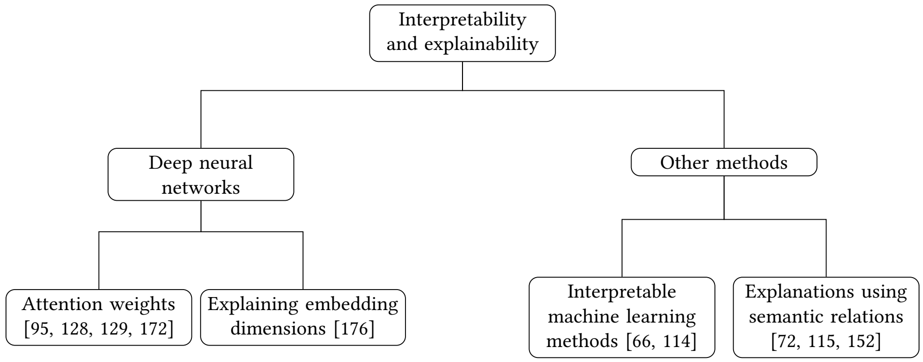

Fig. 5. An overview of the *interpretability and explainability* challenge

Another approach that user preferences are taken into consideration in recommendation is by using **user-defined preferences** specified in the user profile (e.g., interests, location, etc.) [122, 138, 149, 156], or through interactive dashboards [72], conversational apps [14, 18, 19], and explicit questions [22]. Moreover, recruiters can also express their preferences for suitable job seekers by specifying constraints on features of the job seekers [118]. Although many studies have the same approach in the recommendation, we only included the papers that explicitly focus on user preferences in this section.

3.6 Interpretability and explainability

Interpretability often refers to the model's transparency and the ability to understand why and how the model generates the predictions. On the other hand, explainability often refers to the ability to explain the predictions in human terms, even for complex models. However, interpretability and explainability have often been used interchangeably, and we also use the two terms interchangeably in this section. As described in Section 3.1.5, providing explanations for recommendations in e-recruitment is a challenging and important task since the recommendations affect people's future careers and explanations help them make more insightful decisions (HS aspect 2.5). We briefly discuss different approaches proposed in the literature to achieve interpretability and explainability for e-recruitment recommendations in the rest of this section, which includes using methods to provide explainability in deep neural network models, using interpretable machine learning methods, and using explicit relations in data to provide explainability. An overview of the approaches that address interpretability and explainability is presented in Fig. 5.

One way **explainability is addressed in the deep neural models** that use resumes and job descriptions for person-job fit prediction is to visualize the attention weights. The attention weights could show the importance of different words, sentences, or any part of the resume/job description in the resume/job description [128, 129] and also their importance in matching with the target job description/resume words, sentences, or any part of it [95, 128, 129, 172]. Another way to address explainability in deep neural models is proposed by Zhu et al. [176]. For each dimension in the final representation of resumes and jobs resulting from the deep model, high-frequency words were gathered from other resumes and jobs that have high values for that dimension. Hence, a level of explainability was provided for each job posting or resume.

Another approach by which explainability is provided in the literature is by applying **interpretable machine learning methods** such as decision trees to human-readable features [66, 114].

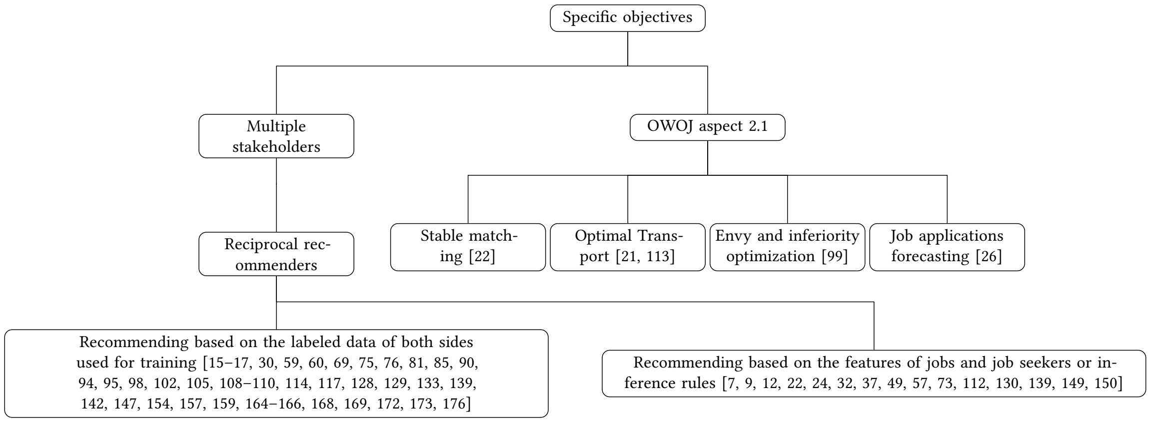

Fig. 6. An overview of the *specific objectives* challenge

In other studies, explainability is provided using **semantic relations**. In [72] a dashboard was provided to view the job seekers' affinity with the required skills for the jobs that are recommended. In [152], recommendations were generated using a knowledge graph together with a template for explainability, where the template was then completed using the nodes in the knowledge graph. Mentec et al. [115] provide explanations by the similarity of job seekers' and job postings' skills using a skill ontology.

3.7 Specific objectives

E-recruitment recommendation systems usually should satisfy multiple stakeholders, such as employers, job seekers, and sometimes the recommendation platform, which benefits from matching job seekers with jobs (TSE aspect 2.2). The platforms' benefits are often included in the job seeker's and employers' benefits since job seekers' and employers' satisfaction also leads to more revenue for the recommendation platform. Hence, most studies try to improve the recommendations for job seekers and employers. In addition, some studies have considered specific objectives for e-recruitment recommendation systems (e.g., OWOJ aspect 2.1). We briefly discuss the papers dealing with such issues that are also described in Section 3.1.6. An overview of this section is presented in Fig. 6.

Since **reciprocal recommenders** recommend job seekers to job postings and vice versa, they usually consider the benefits of job seekers and employers at the same time. Some studies use historical interactions between job seekers and employers that show the interests of both sides for training. The labeled data for such methods usually includes interview and recruitment data [15–17, 30, 60, 69, 75, 76, 81, 85, 94, 95, 98, 102, 105, 109, 114, 117, 128, 129, 133, 142, 154, 157, 159, 164, 165, 169, 172, 173, 176], actions such as favorite, click, apply, review, etc. by both job seekers and recruiters [59, 108, 139, 147, 166, 168], or manually annotated data [90, 110]. On the other hand, some methods compute the matching degree of a job seeker and a job posting based on the similarity of their contents, skills, or other features, or by inference rules [7, 9, 12, 22, 24, 32, 37, 49, 57, 73, 74, 112, 130, 139, 149, 150], which could recommend jobs to job seekers and vice versa with this approach.

Other than the reciprocal nature of recommendation in e-recruitment, some studies have considered the fact that in the job market, for a fixed period of time, each job seeker is hired for one (or a few) job position and vice versa (**OWOJ** aspect 2.1). As a result, avoiding congestion in job recommendation and distributing the jobs equally among

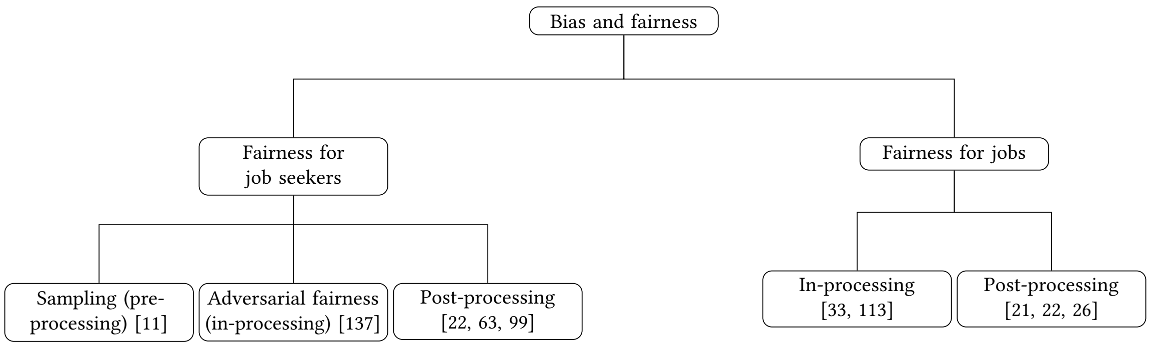

Fig. 7. An overview of the *bias and fairness* challenge

job seekers has been the focus of some studies in the past few years. A stable matching algorithm was employed in [22] to find recommendations for job seekers and recruiters considering this aspect. Some studies use the Optimal Transport theory to equally distribute jobs among job seekers [21, 113]. Moreover, a job application redistribution at LinkedIn was proposed in [26] to prevent job postings from receiving too many or too few applications. To achieve this goal, the job recommendation scores were penalized or boosted based on the predicted number of applications using a dynamic forecasting model. From another perspective, Li et al. [99] proposed a novel fairness concept "inferiority" to address the competition disadvantage faced by job seekers since resources are limited in the job market, and designed a re-ranking approach to reduce envy and inferiority.

3.8 Bias and fairness

The problems related to bias and fairness in AI have gained more attention in recent years. Since e-recruitment affects people's career choices, it is crucial to consider the fairness aspects of the recommendations (HS aspect 2.5): e-recruitment is even defined as one of the high-risk domains according to the EU's AI act (proposal) [38]. Realizing the limitation of pure algorithmic debiasing methods, some researchers have argued that mitigating bias and unfairness in e-recruitment deserves an interdisciplinary point of view involving legal and ethical considerations ([131, 141]). Wang et al. [155] addressed the limitation of current debiasing technology by conducting an online user study showing that biased recommendations are preferred by job seekers, which indicates that human bias should be addressed from new perspectives or new technology.

Multi-Stakeholder Fairness Considerations. E-recruitment systems inherently serve multiple stakeholders [1], including job seekers and employers, each facing distinct fairness concerns. Issues such as racial or gender discrimination against job seekers, as discussed in [101], and popularity bias [2] and selection bias [33] against job postings, etc, illustrate the complex fairness challenges in e-recruitment.

Fairness Mitigation Approaches. Addressing fairness in e-recruitment encompasses three primary strategies: pre-processing, in-processing, and post-processing (re-ranking), each targeting different stages of the recommendation process: **Pre-processing approaches** address fairness issues in the input data by various techniques such as reducing the amount of information on sensitive attributes, balanced sampling to achieve an equal representation of sensitive groups among positive and negative points, etc. **In-processing approaches** address fairness issues by creating inherently fair models by integrating fairness directly into the training process. This can involve developing algorithms

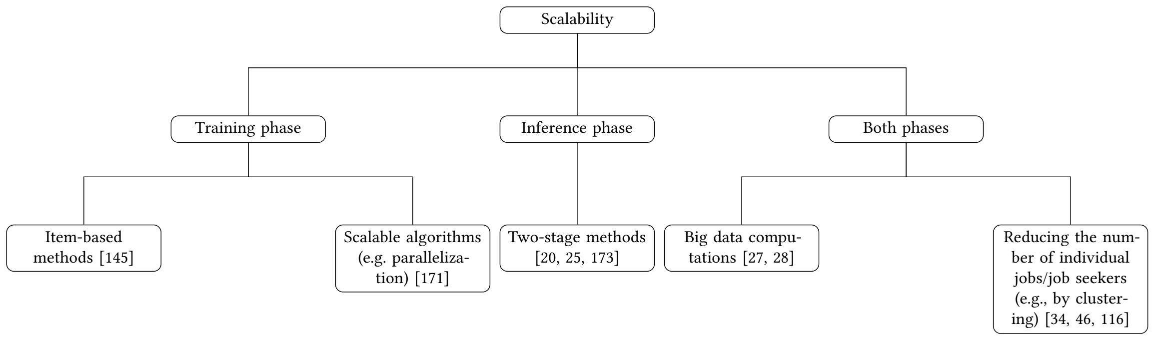

Fig. 8. An overview of the *scalability* challenge

that balance accuracy with fairness criteria. **Post-processing approaches** address fairness issues by adjusting the output of recommendation models to correct for residual biases, typically by re-ranking the generated recommendations by a base model.

We briefly discuss the papers addressing fairness issues, which are also described in Section 3.1.7. We first present the studies focusing on fairness for job seekers and then the papers addressing fairness issues for job postings. An overview of the approaches that address fairness issues in e-recruitment recommendation systems is presented in Fig. 7.

To provide **fair recommendations concerning job seekers**, Arafan et al. [11] proposed a pre-processing approach, where they designed a sampling method to provide a balance between two sensitive groups in the training data. In an in-processing approach, Rus et al. [137] provided debiased embeddings for job seekers through adversarial fairness where they combine a classification task of predicting the industry group of job seekers with the adversarial task of predicting the sensitive attribute of job seekers. The debiased embeddings can then be used in the recommendation task. Several post-processing approaches target fairness for job seekers [22, 63, 99]. Geyik et al. [63] proposed a fairness-aware framework for ranking job seekers as used in search and recommending job seekers. Four deterministic re-ranking algorithms were proposed to mitigate biased prediction towards any sensitive group.

To provide **fairness for job postings**, Chen et al. [33] tackled the recency bias in job recommendation. They considered the recency bias as a type of selection bias imposed by the job seekers and designed an unbiased loss using inverse propensity weighting in a neural collaborative filtering model. To increase the fairness of exposure for jobs in the recommendations generated for the job seekers, Mashayekhi et al. [113] design a multi-objective optimization problem where they combine a base recommendation model with a loss using optimal transport theory. The base recommendation model provides high quality and relevant recommendations, where the optimal transport part avoids congestion in the recommendations and distributes the exposure among the jobs more equally. Bied et al. [21] employ optimal transport theory for the same purpose in a post-processing approach. Other post-processing approaches have been proposed using stable matching algorithms [22] and re-scoring based on the estimation of the number of job applications [26] to provide fairness of exposure for jobs.

This section elaborates on the diverse strategies employed to address bias and fairness in e-recruitment. The recent survey by Fabris et al. [52] further underscores the importance of this topic, providing comprehensive insights into fairness and bias in algorithmic hiring.

3.9 Scalability

Real-world job recommendation systems have to deal with millions of job seekers and job postings. Hence, recommending at large-scale needs to be considered in online job market platforms. We briefly discuss the papers dealing with scalability issues described in Section 3.1.8, which include reducing execution time and consuming storage/memory in the training and inference phases. An overview of the approaches that address scalability issues in e-recruitment recommendation systems is presented in Fig. 8.

To deal with the execution time and consumed storage/memory issues during the **training phase**, a study from CareerBuilder[4] [145] created an item-based graph of jobs with edges representing job similarities based on behavioral and content-based signals. An item-based graph of jobs with different similarity scores was used rather than a user-based (job seeker based) or user-item (job-job seeker) graph for scalability. A subgraph of this job graph was selected by a job seeker's resume or past clicks, and the recommendations were generated by applying the PageRank algorithm to this subgraph. In a study at LinkedIn [171], a scalable algorithm (a parallel block-wise coordinate descent algorithm) was designed for learning the GLMix model to predict the user response.

To deal with the response time in the **inference phase** a two-stage architecture is often used by industry leaders, where the first stage selects a pool of candidates from a large number of items using a computationally inexpensive model, and the second stage re-ranks the results using a more expensive model. One example of the two-stage architecture was designed for recommendation at CareerBuilder [173]. The first stage was designed to select hundreds of candidates from millions using FAISS [87] to find the nearest neighbors of an entity in the embedding space. The embeddings were calculated through three components; a deep neural network to learn from the textual data, a representation framework to learn from three graphs constructed from jobs and skills [39], and a geolocation embedding calculator [105]. The second stage was designed to re-rank the candidates using a weighted linear combination of the first stage scores and context-based scores. In [25], a candidate selection model, CasMoS, was proposed as the first stage in the two-stage recommendation framework at LinkedIn. CasMoS is the framework that learns the first stage model, candidate selection, using the Weighted AND (WAND) query operator [29]. Bied et al. [20] designed a two-stage recommendation system where they use apply and hire interactions to deal with data sparsity and improve the recommendations.

From another perspective, to deal with scalability issues both in the **training and inference phases**, some studies [27, 28] employed Apache Spark, a tool to process big data, to recommend jobs to job seekers using content-based algorithms. Another proposed approach to deal with big data and a large number of entities is to cluster jobs and/or job seekers [34, 46, 116].

3.10 Trends and patterns

While analyzing the papers included in this survey, we identified several trends and patterns in e-recruitment recommendation systems. One notable trend is the emergence of reciprocal recommendation, which gained attention, particularly after 2017, emphasizing mutual preferences between job seekers and employers. Despite reciprocity gaining attention, papers addressing job recommendations outnumber papers recommending job seekers to employers. From another perspective, content-based and hybrid recommendation techniques have been favored approaches in the surveyed papers, leveraging various available facets to deliver personalized recommendations. Additionally, there are fewer papers specifically on the cold start challenge after 2019. Perhaps it has become common knowledge that leveraging available content for the recommendations tackles this problem to some extent. Moreover, within the surveyed papers,

[4] https://www.careerbuilder.com/

there has been a growing emphasis on making recommendation systems more interpretable for users since 2018, while fairness in e-recruitment recommendation systems has become a focal point in papers starting around 2019. These trends underscore the dynamic nature of e-recruitment recommendation systems as observed within the scope of the surveyed literature, reflecting ongoing efforts to enhance performance, transparency, and fairness in the recommendation process.

3.11 Papers not included in previous sections

Some of the collected papers are not included in the previous sections because they did not directly address any of the challenges discussed in this survey [5, 6, 23, 31, 35, 39, 40, 45, 48, 51, 55, 56, 67, 77, 78, 80, 86, 91, 92, 97, 103, 104, 119, 123, 125, 127, 134, 162, 174, 177]. However, some papers tackle a specific challenge in e-recruitment recommendation systems, such as dealing with missing features [86] or applying different recommendation strategies for different groups of job seekers [80, 86]. We did not discuss such challenges in these papers since either there were not many papers dealing with the same issues or these issues were considered to be of lesser practical significance as compared to the challenges highlighted in the present survey. Practical challenges and lessons learned from the e-recruitment recommendation system at LinkedIn are also discussed in two talks [64, 89].

4 CONCLUSION

In this section, we provide our final remarks. We first provide a summary of this survey in Section 4.1. Next, we discuss the limitations of this survey in Section 4.2. Finally, open challenges and future research directions of recommendation in e-recruitment are discussed in Section 4.3.

4.1 Summary

E-recruitment recommendation includes recommending jobs to job seekers and job seekers to jobs. We identified eight challenges that have been studied in the past decade for recommendation in e-recruitment. Since the available data for training an e-recruitment recommendation model include the interactions between job seekers and job positions together with their features and textual contents, several studies have addressed **data quality** issues.

Job seekers' and jobs' data usually include textual content, location, categorical features, etc., which could also be enriched by external data sources. Moreover, there are many interaction types, such as click, apply, invite, chat, interview, etc., in e-recruitment platforms. Therefore, dealing with **heterogeneous data, and multiple interaction types and data sources** is another challenge in e-recruitment.

Since job positions with the same content are often represented as different entities in e-recruitment recommendation systems (different job entities with distinct IDs may have the same title/content), **cold start** problem needs more attention in e-recruitment recommendation compared to the traditional recommenders. The availability of many facets in the e-recruitment domain could help alleviate the cold start problem.

Traditional recommendation systems mainly consider user preferences for generating the recommendations, while e-recruitment recommendation systems have to match job seekers with jobs based on the job seekers' skills and jobs' required skills as well. Hence, e-recruitment recommendation systems should consider **user preferences as well as suitability**.

Explainable recommendations in general help users make better decisions. Nonetheless, **interpretability and explainability** are even more important in e-recruitment recommendation systems since e-recruitment recommendation has a great influence on job seekers' future careers and also on the employers of companies.

Recommendation systems in a specific domain could have **specific objectives**. In e-recruitment, the goal is usually to satisfy multiple stakeholders, including job seekers, recruiters, and service providers. Moreover, e-recruitment recommendation systems should consider the fact that each job seeker could be employed for one or a few job positions and vice versa, which can introduce new objectives for recommendation systems.

Bias and fairness issues are challenging for most recommendation systems. In e-recruitment, it is even more critical to provide fair recommendations due to the possible high-stakes involved for both job seekers and employers.

Finally, **scalability** issues cannot be ignored in designing real-world recommendation systems. Since e-recruitment recommendation systems usually have to provide services for thousands/millions of job seekers and job positions, they have to consider the scalability aspect of the recommendation system.

4.2 Limitations of the survey

We have selected and elaborated the main challenges in the e-recruitment recommendation from our point of view, but there could be other challenges in this domain. For example, extracting features from textual data with different granularity could also be considered as another challenge, albeit not specific to the e-recruitment domain. Identifying more challenges and categorizing papers based on their approaches to address them remain for the future.

Since e-recruitment recommendation could be a reciprocal recommendation task (recommending jobs to job seekers and vice versa), reviewing the challenges in other reciprocal recommendation systems (e.g., online dating) could also be useful for designing e-recruitment recommendation systems. We omitted papers from other reciprocal recommendation domains to limit the scope of this survey.

4.3 Open challenges and future research directions

While there has been much useful work in addressing certain aspects of e-recruitment recommendation systems, there are still some open challenges in this domain that could be investigated in future research works. Some of such challenges that we personally consider promising include:

- **One worker, one job** (OWOJ aspect 2.1). Since each job seeker can only be employed for one or a few jobs and a job can be assigned to one or a few candidates, balancing the recommendations in a way that job postings do not receive too many or too few applications is of great importance. Moreover, each job/job seeker should receive recommendations with a high chance of success. This would require the recommendation system to consider the relative probability of matching, that is, how likely one's recommended jobs would be successfully matched with other job seekers. Although some aspects of these issues have been addressed in a few papers (see Section 3.7), this challenge still needs further investigation for more insights and new solutions.
- **Career path recommendation**. Some job seekers choose their next jobs in a way that helps them reach their dream jobs in the future. This problem has been addressed by a few career path recommendation systems, which recommend intermediate jobs to reach the final career goal [65]. This line of research could be investigated in future studies.
- **Domain adaptation**. Domain adaptation techniques can improve model performance with limited labeled data, but the application of such techniques in e-recruitment recommendation has not been well investigated except for in a few studies such as [16]. Methods for domain adaptation between different job sectors, languages, platforms, countries, etc., would be worth investigating to improve the performance of e-recruitment recommendation systems.

- **Multi-linguality**. Many platforms/countries have resumes and job postings in multiple languages. Hence, e-recruitment recommendation systems in those platforms/countries should support multiple languages and cross-matching resumes and job postings with different languages. Although some papers have addressed this problem (see Section 3.2), further investigations are still in need to provide better support for multi-lingual platforms.
- **Conversational**. Conversational recommendation systems perform multi-turn dialogue with users to achieve recommendation-related goals [84]. Although conversational recommendation systems have become more popular in recent years [61], few studies have explored conversational settings in the e-recruitment domain [14, 18, 19, 115]. A conversational recommendation can elicit the current user's preference, provide explanations, make use of explicit feedback, etc., which makes it valuable to e-recruitment and worthwhile for future studies [61].
- **Specific job seekers**. Some groups of job seekers may need special attention by e-recruitment recommendation systems. First, user interfaces need to be designed specifically for certain user groups to enhance their interactions with the system (e.g., for people with special needs). This aspect should also be considered for some groups of recruiters. Moreover, some groups of job seekers might be fit for some specific jobs. For example, adults with autism are among the most under employed demographics [22]. However, they have special skills to contribute to the workplace if applied to the right job [22]. Although there have been some job recommenders designed for *specific job seekers* such as students and new graduates [55, 89, 106–108, 125, 144, 151, 156, 174], the elderly [12], migrants and refugees [122], and people with special needs [22, 148], exploring the needs of more subgroups of job seekers could greatly benefit the e-recruitment field. More specifically, designing a taxonomy of different groups of job seekers with their characteristics and needs would be a good starting point, which could further encourage collecting data for designing recommendation methods that can take the differences between different groups of job seekers into consideration.
- **Fairness**. Fair recommendation in e-recruitment is even more important than that in other recommendation systems because people's career choices are influenced by their recommended jobs and the recommendation may also have a long-term impact on the labor market (HS aspect 2.5). Although there has been growing attention to fairness issues in general recommendation settings, not many papers specifically address these issues in e-recruitment recommendation systems (as shown in Section 3.8). One reason could be that the fairness issues are more complicated than the other recommendation systems due to the reciprocal nature and multiple stakeholders involved in e-recruitment. Another reason might be that there are relatively few open datasets for this specific field, as elaborated below.

One important future research direction in e-recruitment recommendation systems is navigating their legal implications, which vary across countries. Consequently, some topics such as fairness and explainability require more attention in the future to ensure e-recruitment recommendation systems align with legal standards.

Another challenge in research for e-recruitment recommendation systems is that few public datasets are available. As far as we know, there are only two public datasets: *CareerBuilder 2012 dataset*[5] on Kaggle[6] from the e-recruitment platform CareerBuilder[7] and *Zhilian dataset*[8] from a Chinese e-recruitment platform Zhilian[9]. The two datasets for the

[5]https://www.kaggle.com/c/job-recommendation
[6]https://www.kaggle.com/
[7]https://www.careerbuilder.com/
[8]https://tianchi.aliyun.com/dataset/dataDetail?dataId=31623
[9]https://www.zhaopin.com

RecSys challenges 2016 [3] and 2017 [4] provided by the e-recruitment platform Xing[10], although used in some related studies, are not publicly available. Advances in e-recruitment recommendation systems from academic research depend on the availability of public datasets: more publicly available data could help to establish stronger benchmarks; larger datasets of variety could also facilitate new ideas to appear in the field.

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A SUPPLEMENTARY MATERIALS

Table 1 gives an overview of all the papers that have been collected with the literature search methodology in Section 1.2.

Table 1. An overview of e-recruitment recommendation systems is presented. Regarding the recommended entities, although some papers could be reciprocal in design, we did not report them as reciprocal since they did not claim to be reciprocal and also they only experimented with the job or job seeker recommendation task. The methods cover a broad range of content-based (CB), collaborative filtering (CF), knowledge based (KB), and hybrid/other methods. Some papers focus on preprocessing, re-ranking, or design a generic framework, and do not mention the recommendation method type in detail. Hence, we also do not report the recommendation method type for those papers. The papers are sorted based on their publication year.

Paper	Year	Recommended entities			Method				Challenge							
		Job	Job seeker	Reciprocal	CB	CF	KB	Hybrid/Other	3.2 Data quality	3.3 Heterogenous data, multiple interaction types and data sources	3.4 Cold start	3.5 User preferences as well as suitability	3.6 Interpretability and explainability	3.7 Specific objectives	3.8 Bias and fairness	3.9 Scalability
[24]	2012	○	○	●	○	○	○	●	○	●	○	○	○	●	○	○
[54]	2012	○	●	○	●	○	○	○	○	●	○	○	○	○	○	○
[80]	2013	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[117]	2013	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[108]	2013	○	○	●	○	○	○	●	○	●	○	○	○	●	○	○
[43]	2013	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[79]	2013	●	○	○	○	○	○	●	○	○	●	○	○	○	○	○
[71]	2014	●	○	○	○	○	○	●	○	○	●	○	○	○	○	○
[44]	2014	●	○	○	○	○	○	●	●	●	○	○	○	○	○	○
[42]	2014	●	○	○	○	○	○	●	●	○	○	○	○	○	○	○
[111]	2014	●	○	○	●	○	○	○	○	●	○	○	○	○	○	○
[77]	2014	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[53]	2014	○	●	○	○	○	○	●	●	●	○	○	○	○	○	○
[6]	2014	○	●	○	●	○	○	○	○	○	○	○	○	○	○	○
[7]	2015	○	○	●	●	○	○	○	○	○	○	○	○	●	○	○
[37]	2015	○	○	●	○	○	○	●	○	●	○	○	○	●	○	○
[74]	2015	○	○	●	○	○	●	○	●	○	○	○	○	●	○	○
[139]	2015	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[35]	2015	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[104]	2016	●	○	○	○	○	○	●	○	○	○	●	○	○	○	○
[170]	2016	●	○	○	○	○	○	●	○	●	●	○	○	○	○	○
[106]	2016	●	○	○	○	○	○	●	○	●	●	○	○	○	○	○
[45]	2016	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[31]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[97]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[119]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[123]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[40]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[127]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[162]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[177]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[96]	2016	●	○	○	○	○	○	●	●	○	●	○	○	○	○	○
[70]	2016	●	○	○	○	○	○	●	●	●	○	○	○	○	○	○
[130]	2016	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[143]	2016	●	○	○	○	○	○	●	●	○	●	○	○	○	○	○
[103]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[25]	2016	●	○	○	●	○	○	○	○	○	○	○	○	○	○	●
[171]	2016	●	○	○	○	○	○	●	○	○	○	○	○	○	○	●
[5]	2017	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[145]	2017	●	○	○	○	○	○	●	●	○	●	○	○	○	○	●
[132]	2017	●	○	○	○	●	○	○	○	○	○	○	○	○	○	○
[107]	2017	●	○	○	○	○	○	●	○	●	●	○	○	○	○	○
[167]	2017	●	○	○	○	○	○	●	○	○	●	○	○	○	○	○
[13]	2017	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[89]	2017	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[12]	2017	○	○	●	●	○	○	○	○	○	○	○	○	●	○	○
[32]	2017	○	○	●	●	○	○	○	○	●	○	○	○	●	○	○
[144]	2017	●	○	○	○	○	○	●	○	○	●	○	○	○	○	○
[46]	2017	●	○	○	○	○	○	●	●	○	○	○	○	○	○	●
[164]	2017	○	○	●	○	○	○	●	○	○	●	○	○	●	○	○
[142]	2017	○	○	●	●	○	○	○	○	○	●	○	○	●	○	○
[125]	2017	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○

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[69]	2017	○	○	●	●	○	○	○	○	○	●	○	○	●	○	○
[102]	2017	○	○	●	●	○	○	○	○	○	●	○	○	●	○	○
[17]	2017	○	○	●	○	○	○	●	○	○	●	○	○	●	○	○
[154]	2017	○	○	●	○	○	○	●	○	●	●	○	○	●	○	○
[26]	2017	●	○	○	○	○	○	○	○	○	○	○	○	●	●	○
[78]	2018	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[50]	2018	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[153]	2018	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[39]	2018	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[66]	2018	●	○	○	●	○	○	○	○	○	○	○	●	○	○	○
[163]	2018	○	●	○	○	○	○	●	●	○	○	○	○	○	○	○
[110]	2018	○	○	●	●	○	○	○	○	○	○	○	○	●	○	○
[176]	2018	○	○	●	●	○	○	○	○	○	○	○	●	●	○	○
[128]	2018	○	○	●	●	○	○	○	○	○	○	○	●	●	○	○
[34]	2018	●	●	○	○	○	○	●	●	○	●	○	○	○	○	●
[67]	2019	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[134]	2019	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[148]	2019	●	○	○	○	○	●	○	●	○	○	○	○	○	○	○
[120]	2019	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[121]	2019	●	○	○	○	○	○	●	○	○	●	●	○	○	○	○
[72]	2019	●	○	○	○	○	●	○	○	○	○	●	●	○	○	○
[86]	2019	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[33]	2019	●	○	○	○	●	○	○	○	○	○	○	○	○	●	○
[105]	2019	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[92]	2019	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[135]	2019	○	●	○	●	○	○	○	●	●	○	○	○	○	○	○
[56]	2019	○	●	○	●	○	○	○	○	○	○	○	○	○	○	○
[165]	2019	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[112]	2019	○	○	●	○	○	●	○	●	○	○	○	○	●	○	○
[95]	2019	○	○	●	○	○	○	●	○	○	○	○	●	●	○	○
[16]	2019	○	○	●	●	○	○	○	○	○	○	○	○	●	○	○
[109]	2019	○	○	○	●	○	○	○	○	●	○	○	○	●	○	○
[63]	2019	○	●	○	○	○	○	○	○	○	○	○	○	○	●	○
[116]	2020	●	○	○	○	○	○	●	○	○	○	○	○	○	○	●
[93]	2020	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[68]	2020	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[14]	2020	●	○	○	●	○	○	○	●	○	○	●	○	○	○	○
[158]	2020	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[90]	2020	○	○	●	●	○	○	○	●	○	○	○	○	●	○	○
[98]	2020	○	○	●	●	○	○	○	○	○	○	○	○	●	○	○
[23]	2020	○	●	○	●	○	○	○	○	○	○	○	○	○	○	○
[57]	2020	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[129]	2020	○	○	●	○	○	○	●	○	○	○	○	●	●	○	○
[85]	2020	○	○	●	●	○	○	○	○	○	○	○	○	●	○	○
[27]	2020	○	●	○	●	○	○	○	●	○	○	○	○	○	○	●
[136]	2020	○	●	○	●	○	○	○	●	○	○	○	○	○	○	○
[146]	2020	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[15]	2020	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[55]	2021	●	○	○	○	○	○	●	○	○	○	○	○	○	○	○
[19]	2021	●	○	○	○	○	○	●	○	○	○	●	○	○	○	○
[18]	2021	●	○	○	○	○	○	●	○	○	○	●	○	○	○	○
[115]	2021	○	●	○	○	○	○	●	●	○	○	○	●	○	○	○
[152]	2021	●	○	○	○	○	○	●	○	○	○	○	●	○	○	○
[174]	2021	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[22]	2021	○	○	●	○	○	○	●	○	○	○	●	○	●	●	○
[94]	2021	○	○	●	●	○	○	○	●	○	○	○	○	●	○	○
[157]	2021	○	○	●	○	○	○	●	○	○	○	○	○	●	○	○
[73]	2021	○	○	●	○	○	○	●	●	○	○	○	○	●	○	○

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[49]	2021	○	○	●	●	○	○	○	○	●	○	○	○	●	○	○
[150]	2021	○	○	●	●	○	○	○	●	○	○	○	○	●	○	○
[60]	2021	○	○	●	○	○	○	●	○	●	○	●	○	●	○	○
[173]	2021	○	○	●	○	○	○	●	○	●	○	○	○	●	○	●
[172]	2021	○	○	●	●	○	○	○	○	○	○	○	●	●	○	○
[114]	2021	○	○	●	●	○	○	○	●	○	○	○	●	●	○	○
[149]	2021	○	○	●	●	○	○	○	○	○	○	●	○	○	○	○
[10]	2021	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[75]	2021	○	○	●	●	○	○	○	○	●	○	○	○	●	○	○
[76]	2021	○	○	●	●	○	○	○	○	●	○	○	○	●	○	○
[30]	2021	○	○	●	○	○	○	○	○	○	○	○	○	●	○	○
[83]	2021	●	○	○	○	●	○	○	○	●	○	○	○	○	●	○
[21]	2021	●	○	○	○	○	○	○	○	○	○	○	○	●	●	○
[8]	2022	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[151]	2022	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[36]	2022	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[28]	2022	○	●	○	●	○	○	○	○	○	○	○	○	○	○	●
[166]	2022	○	○	●	○	○	○	●	○	○	○	○	○	○	○	○
[51]	2022	●	○	○	●	○	○	○	○	○	○	○	○	○	○	○
[118]	2022	○	●	○	●	○	○	○	○	○	○	●	○	○	○	○
[137]	2022	●	○	○	●	○	○	○	○	○	○	○	○	○	●	○
[59]	2022	○	○	●	○	○	○	●	○	●	○	○	○	○	○	○
[159]	2022	○	○	●	○	○	○	●	○	○	○	○	○	○	○	○
[168]	2022	○	○	●	○	○	○	●	●	●	○	○	○	○	○	○
[81]	2022	○	○	●	○	○	○	●	○	○	○	○	○	○	○	○
[88]	2022	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[169]	2022	○	○	●	○	○	○	●	●	○	○	○	○	○	○	○
[126]	2022	○	●	○	●	○	○	○	○	●	○	○	○	○	○	○
[138]	2022	●	○	○	○	○	○	●	○	●	○	●	○	○	○	○
[9]	2022	○	○	●	●	○	○	○	●	○	○	○	○	○	○	○
[122]	2022	●	○	○	○	○	○	●	○	●	○	●	○	○	○	○
[11]	2022	○	●	○	●	○	○	○	○	○	○	○	○	○	●	○
[160]	2023	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[20]	2023	●	○	○	○	○	○	●	●	●	○	○	○	○	○	●
[156]	2023	●	○	○	○	○	○	●	○	○	○	●	○	○	○	○
[82]	2023	●	○	○	○	○	○	●	○	●	○	○	○	○	○	○
[47]	2023	●	○	○	○	○	○	●	●	○	○	○	○	○	○	○
[113]	2023	●	○	○	○	○	○	○	○	○	○	○	○	●	●	○
[99]	2023	●	○	○	○	○	○	○	○	○	○	○	○	●	●	○
[91]	2023	●	○	○	○	●	○	○	○	○	○	○	○	○	○	○
[175]	2023	●	○	○	●	○	○	○	●	○	○	○	○	○	○	○
[147]	2023	○	○	●	○	○	○	●	●	●	○	○	○	○	○	○
[133]	2023	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○