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SURVEY PAPER

e-Recruitment recommender systems: a systematic review

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Abstract

Recommender Systems (RS) are a subclass of information filtering systems that seek to predict the *rating* or *preference* a user would give to an item. e-Recruitment is one of the domains in which RS can contribute due to presenting a list of interesting jobs to a candidate or a list of candidates to a recruiter. This study presents an up-to-date systematic review of recommender systems applied to e-Recruitment considering only papers published from 2012 up to 2020. We searched three databases for published journal articles, conference papers and book chapters. We then evaluated these works in terms of which kinds of RS were applied for e-Recruitment, what kind of information was used in the e-Recruitment RS, and how they were assessed. A total of 896 papers were collected, out of which sixty three research works were included in the survey based on the inclusion and exclusion criteria adopted. We divided the recommender types into five categories (Content-Based Recommendation 26.98%; Collaborative Filtering 6.35%; Knowledge-Based Recommendation 12.7%; Hybrid approaches 20.63%; and Other Types 33.33%); the types of information used were divided into four categories (Social Network 38.1%; Resumés and Job Posts 42.85%; Behavior or Feedback 12.7%; and Others 6.35%), and the assessment types were categorized into four types (Expert Validation 20.83%; Machine Learning Metrics 41.67%; Challenge-specific Metrics 22.92%; and Utility measures 14.58%). Although in many cases a paper may belong to more than one category for each evaluation axis, we chose the most predominant one for our categorization. In addition, there is a clear trend for hybrid and non-traditional techniques to overcome the challenges of e-Recruitment domain.

Keywords e-Recruitment · Job recommender systems · Systematic review · Recommendation methods

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1 Introduction

E-Recruitment Platforms emerged as a feasible solution to help with the problem of allocating professionals, decreasing the recruitment time and advertisement costs, but, at the same time, increasing the data volume with which the Human Resource Management professionals must deal with.

Recommender Systems (RS) have, for long, been applied to help users finding items (e.g., goods or services) that match their personal interests [7]. RSs are information filtering systems that deal with the information overload problem by filtering relevant pieces of information from dynamically generated data and by capturing users' preferences, interests, or observed behaviors about items. They can predict at what extent a particular user would prefer an item among others based on his profile [13,39,55,59].

The utility of a recommendation is proportional to the difficulty of discovering an item by a specific user in a determined context. Let us, for instance, imagine a scenario without such recommendation resource. A user retrieves a large number of items to select and deciding about the relevant ones. This is a time-consuming activity and frustrates the user by the overload of information. Processing this volume of information is a tedious time-consuming task. However, putting all trust on a machine curated list can also frustrate the user if the selected items are not relevant or if the user discovers by himself highly relevant items not filtered and recommended to him.

There are several known limitations in RSs depending on the employed approach, such as [2]:

(a) *Limited content analysis* content-based techniques are limited by the features explicitly associated with the items these systems recommend, and another problem is if two different items are represented by the same set of features, they are indistinguishable;
(b) *Over-specialization* when the system can only recommend items that score highly against a user's profile, the user is limited to being recommended items similar to those already rated;
(c) *New user problem* the user has to rate a sufficient number of items before a recommender system can really understand the user's preferences and present him with reliable recommendations;
(d) *New item (cold start) problem* new items are added regularly to the RS and a recommendation has to be made without the item's history; and
(e) *Sparsity* the number of ratings already obtained is usually very small when compared with the number of ratings needed to make a recommendation.

This paper aims to provide the first systematic review of Recommender Systems applied to e-Recruitment (eRRS) and Job Recommender Systems (JRS) and is focused on verifying novel approaches, technologies and methods to overcome the problems outlined above. The review is performed around three key research questions that are the core of an effective e-Recruitment recommender design: (1) type of recommendation engine; (2) type of information used as input to the system; and (3) how the recommender is assessed. For each of these questions we devise and explain a categorization method, placing the works in those categories that are predominant in each of them. It is important to recognize, however, that many works may fall into more than one category, but we chose to place them in the single most predominant one such that we can have a clearer view of the papers' distribution over the categories.

The remaining of this paper is organized as follows. Section 2 contextualizes the application of Recommender Systems for e-Recruitment. Section 3 describes the systematic review protocol, including the search method, research questions and the inclusion/exclusion criteria for the retrieved papers. Section 4 performs the review itself based on the three research questions raised. Some final remarks are presented in Sect. 5 considering not only the review presented, but also some trends and open research avenues in the field.

2 A briefing on recommender systems for e-Recruitment

In [55], the authors proposed a taxonomy for recommender system applications based on eight broad areas: (1) e-commerce; (2) e-library; (3) e-learning; (4) e-government; (5) e-group; (6) e-tourism; (7) e-resource services; and (8) e-business. Within the e-business area are e-Recruitment recommendation systems, which are usually integrated with e-Recruitment platforms. Additionally, in [75] it is researched the usefulness of some features on several platforms.

Typically, recommendation systems produce a score, known generically as *utility*, for items to choose from, or a list of the *N* most recommended or highest score items [19].

The problem of matching jobs and candidates can be seen from two distinct perspectives: (a) find relevant candidates to a job opening; and (b) select the suitable jobs to a specific candidate. Regardless of the recommendation focus and the approach used, it is common sense that USER is the term designed to receive a set of objects recommended to it and ITEM is one of the objects recommended to a specific user. In addition, a RS designed for both perspectives is known as a bidirectional recommender system [58] and treats interchangeably users and items in a single solution. It can also be found approaches that build ensembles, combining different techniques forming a bidirectional recommender system [40,72,84]. Finally, recommender systems which take into consideration a context are known as (CARS) *Context Aware Recommender System* [88], which filter a set of recommended items based on context criteria.

In [7], the authors summarize the recruitment process, the categories of e-Recruitment platforms and present approaches to run the job-candidate recommendation, their characteristics and challenges. The first approach is **Collaborative Filtering (CF)**, which captures information based on historic logs of users to infer their needs, but suffers from the cold-start problem as the main challenge. The second approach is **Content-Based Recommendation (CBR)**, which is based on the comparison between features of USERs and ITEMs. The two main tasks related to CBR are: (a) the USER profiling; and (b) the ITEM representation. Its limitation lies in the existence of enough and normalized features to measure their similarity. The third approach is called **Knowledge-Based Recommendation (KBR)**, which is based on heuristics that can be built by domain specialists. The limitation of KB recommendation is related to engineering solutions and its scalability. In addition to all these approaches there is a set of solutions called **Hybrid**, which mix other techniques together in order to overcome the problems of single approaches, delivering better results. Such systems are classified as: (1) *Weighted*, in which the score of the item recommendation is calculated weighing the results of each technique used; (2) *Switching*, which uses some measure to switch between recommendation techniques; (3) *Mixed*, which applies various methods simultaneously; (4) *Feature Combination*, which incorporates CF as an additional feature in a CBR technique; (5) *Cascade*, in which one technique serves as a refinement of another to present the final recommendation; (6) *Feature Augmentation*, in which one technique produces ratings that are then processed by another technique; and (7) *Model*, where the output of one technique is used as the input for another. The review also summarizes the current techniques and their pros and cons. The authors of this review have some related works on this topic [3–6].

The e-Recruitment RS differs from traditional RS domains, like e-commerce or entertainment, because instead of simply evaluating the attractiveness of the recommended products, the user-item relationship is ephemeral, contextual and has prerequisites of different dimensions. The first set of prerequisites has to do with demographic issues, the second with technical knowledge, the third with the affinity of common interests, and the fourth with its temporal sensitiveness. Thus, it is not a straightforward scenario to establish a successful match.

Another form of thinking about the integration between users and items, jobs and candidates in our domain, is by comparing similarity among users (user-to-user) and among items (item-to-item), which allows to perform indirect recommendations. By borrowing ideas from the e-commerce domain, such as in [50], it is possible to calculate the similarity between items, and those which are quite similar are good candidates to be recommended to the user. For instance, a job (item) to which a candidate applied is a reasonable manifestation of his interest for that position and can be used to recommend similar jobs to that user.

In summary, to design an eRRS it is necessary to define the following:

1. *Type of recommendation engine* as discussed, a RS can be based on content, collaborative, knowledge-based or hybrid. Thus, one crucial step is to define the types of recommendation methods employed to deliver suitable results.
2. *Input data* what type of information will be input into the system. This list may include three main groups: (a) a combination of content extracted from resumés and public profiles; (b) a set of observed behaviors collected as implicit and explicit feedback during the interaction of a user with a specific item; and (c) models to predict the candidate next move. Depending on the type of input data available, a specific recommendation engine can be used.
3. *Assessment method* assessing a recommender system is a final and necessary step to check if it performs as required and expected. The utility of the generated recommendations needs to be assessed in order to verify the suitability of the methods designed. This utility can be measured as some specific KPIs, for instance: (a) how many recommended candidates evolved to a deeper step into the recruitment process; (b) how many recommended candidates were hired; (c) what is the percentage of irrelevant recommendations in relation to the total recommendations.

A number of previous research reviews have been made about this subject: [1,7,12,21,23, 30,32,46,49,68,70,76,79,82,83,86,97]. However, these are mostly focused on specific aspects of e-Recruitment and/or Job recommendations, and none of them is a Systematic Review. This paper aims to provide an updated systematic extension of what has been researched so far, categorizing the papers by the main approach employed, the information needed to make recommendations and their evaluation methods.

3 Survey method

This section presents a systematic review of the literature aiming to elucidate the body of knowledge and the state of the art regarding approaches to recommend jobs to candidates and/or vice versa. The main research questions used were those that cover our design guidelines:

1. Which type of Recommender System is being applied for e-Recruitment?

Table 1 Search words and number of papers retrieved for each search source used

	Google Scholar	Scopus	Crossref	Total
Title contains: e-Recruitment	59	4	312	375
Keywords: Recommender system				
Time range: 2012–2020				
Title contains: Job recommendation	77	44	400	521
Keywords: Recommender system				
Time range: 2012–2020				
Total	136	48	712	896

2. What kind of information is used in the eRRS to perform the recommendation?
3. How the e-Recruitment Recommender System was assessed?

A. Research source

The sources of search were: (1) Google Scholar; (2) Scopus; and (3) CrossRef. The searches took place on January 2020 and aimed to capture papers related to e-Recruitment Recommender Systems and Job Recommender Systems. This survey only considered papers published between 2012 and 2020. Table 1 presents the queries executed and how many items were retrieved. The data collected were leveraged by the use of the Software Publish or Perish [33], and by using such resource, it was possible to export the results to a CSV file and easily compare the results.

B. Inclusion and exclusion criteria

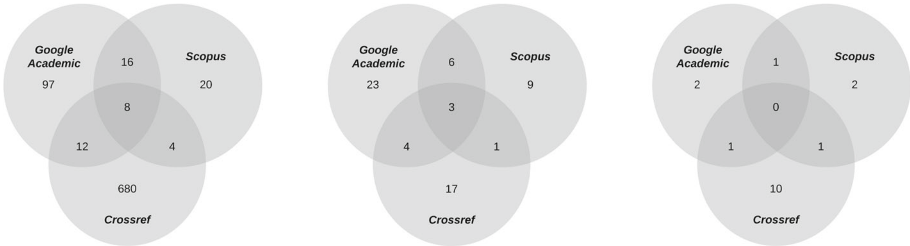
Once obtained a list of papers, the next step was to select those that would be part of the review based on the following criteria:

1. *Unique papers* compared common papers returned from more than one data source;
2. *Title analysis* by reading the titles of the papers, it is possible to verify if they match the presented research questions, only those related with them were selected for review and papers written in English or Portuguese;
3. *Not a review* other surveys were removed;
4. *Relevance* only papers with citations or recent publications (from 2018 onward);
5. *Type* only considering papers published in journals, conferences or book chapters.
6. *Abstract analysis* reading the abstract by two independent reviewers (MNF and LNdC). Conflicts between reviewers were resolved by consensus and removed all papers not related with the theme and papers which not present a proposal (primary research).

Table 2 presents the results and number of papers remained after the application of each filter, and Fig. 1 presents a summary of the papers retrieved during the search, the number of papers eligible to be reviewed based on the inclusion/exclusion criteria and the number of previous reviews available in the literature. According to the selection criteria, only 7.03% of the returned papers are eligible.

Table 2 Number of papers remaining after each criterion

Criterion	Detail	# Papers
1st	Unique papers	832
2nd	Title analysis	236
3rd	Not a review or survey	219
4th	Cited or recent papers (+2018)	183
5th	Type (only: (J)ournal, (C)onferences or (B)ook-chapter)	115
6th	Abstract analysis	63



(a) Total **(b)** Relevants **(c)** Other Surveys

Fig. 1 Analysis of the intersection of retrieved papers from different repositories

4 A systematic review

This section is organized according to the research questions. Firstly, it is summarized and presented the papers according to their recommender method. Then, by the information set and, finally, by the evaluation method employed.

A. Recommendation methods

The recommendation can be made using different techniques and can only be based on the most similar available items, the demographic distribution of users, the most traded items, or the consumption habit of one or more users. In papers [2,55,59], the authors define the main approaches on recommender systems for e-recruitment as follows:

– *CBR* (Content-Based Recommendation), which compares the similarity among data extracted from job posts with candidates' attributes.
– *CF* (Collaborative Filtering recommendation), which identifies similarities among users and/or items inferring a similarity based on an observed behavior rather than on the data per se.
– *Hybrid*, which is a combination between the first two techniques, trying to overcome their individual limitations.
– *KBR* (Knowledge-Based Recommendation), which relies on deep knowledge about the product domain (job) to figure out the best items (job vacancies) to recommend to a user (candidate). It can also use ontologies to contextualize information and leverage the match. It is considered a specialized CBR.

Table 3 List of selected papers categorized by year and recommendation method

Method/year	CBR	CF	HYBRID	KBR	OT
2012	[27,29]				
2013	[22]		[36]		
2014	[23,28,34,57]			[61]	[31,91]
2015	[56,90]			[16,44,45]	[77,92]
2016	[9,65]	[42,53]	[47,52,66,71,96]	[24,26]	[51,63,69,89,93]
2017	[54]	[73]	[18,48,94]		[11,14,25,95]
2018	[10,41,85]		[35]		[15,17,62,80]
2019	[8,64]	[98]	[20,37,38]	[60,81]	[43,67,74]
2020					[87]

CBR content-based recommendation, *CF* collaborative-filtering, *KBR* knowledge-based recommendation, *OT* other types

– *OT* (Other Techniques), which rely on non-traditional approaches to recommend jobs to candidates, and vice versa.

These approaches have pros/cons and, particularly in the e-Recruitment domain, limitations arise preventing the system's stability. The plethora of recent novel approaches combined with non-traditional proposals is an indication of the need for better solutions. Table 3 presents the selected papers organized by year and its recommendation method.

Content-Based Recommenders (CBR) essentially use information gathered from candidates and computes its similarity with the information from a job post. A common source of information about job candidates is their resumés. Thus, the methods usually rely on the ability to cross information among sources in semantically effective way. Several techniques and algorithms can be employed to compute similarities. In [41] a Word2Vec model is proposed. In [9], it is introduced an algorithm that expands and eases the use of the Minkowski distance to match jobs and candidates. In [90] it is proposed a mobile implementation to obtain the cross-similarity value which categorizes jobs and candidates features as: (a) self-description; and (b) preferences; with a one-to-one cross-correspondence between them. In [34], it is computed the cosine similarity in a model that uses job transitions trained over candidates career progressions. As proposed in [56], the corpus of a job offer can be enriched by common terms and then optimize the match capabilities. Other researches, like [57], contribute by helping to select the right fields used on the match from others to be ignored. In [10] it is proposed an approach to match attributes on a more flexible form, starting from the exact match to a range, or even with upper and lower limits.

Nowadays the information to support the candidates abilities' can also be captured beyond resumés. Professional Social Networks (PSN) play crucial roles in the e-Recruitment ecosystem: job boards; interaction among users; endorsement of skills; among others. Together with Applicant Tracking Systems (ATS) they allow a widespread dissemination of opportunities and automate the application and selection processes from a very tedious task to just a few clicks. PSNs are a tremendous source of content about professional achievements, expertise and endorsements and cannot be neglected by any modern recruitment approach. In [23], some experiments were conducted to recommend relevant jobs to Facebook and LinkedIn users. The information was gathered and encoded into three distinct vectors: (a) Facebook user vector containing a set of vectors from Work, Education, Bio, Quotes and Interest fields; (b) a LinkedIn user vector containing a set of vectors from Headline, Educations and Posi-

Table 4 Description of the main hybridization methods available in the literature

Hybridization method	Description
Weighted	Scores of several recommendations are combined to produce a single recommendation
Switching	The system uses some criteria to switch between recommendation techniques.
Mixed	First a content-based method is used for textual description and then a collaborative method finds the preferences of the user. Recommendations from the two techniques suggest a final ranking
Feature combination	Features from different recommendation data sources are used together in a single recommendation algorithm. It considers collaborative data without relying on it exclusively and have information about the inherent similarity of items that are otherwise opaque to a collaborative system
Feature augmentation	A technique is used to rate an item and that information is then incorporated into the processing of the next recommendation technique
Cascade	It involves the stage process where one recommendation technique is employed to produce a ranking of candidates and a second technique refines the recommendation from the candidate set
Meta-level	Two recommendation techniques can be merged by using the model generated by one as the input for another

tions' fields; and (c) a Job vector containing a set of vectors from Title, Description and Responsibilities fields. As suggested in [85], to capture insights about a specific user in a hiring process, valuable information is generated by screening the user's profile to identify soft and hard skills, personality, political opinions, interests and social status. Other works that propose the use of social media profiles to perform recommendation were presented in [27–29]. Finally, in [8,64] geolocation is used as information to recommend jobs.

Collaborative Filtering (CF) is interested in capturing interests based on observable behavior. In situations where the candidate lacks professional history and endorsements, strategies based on content are useless. The paper [53] tackles the problem of recommending jobs to students by calculating similarities among students and when a student receives an offer and rates a company, the system can predict the rate and infer the possibility of match between that company and the similar students. In [98], it is proposed an algorithm to obtain the students' preferences to generate a Bayesian personalized ranking. In addition, the study available in [73] compares and reveals that implicit feedback data covers a broader spectrum of job seekers' job interests than explicitly stated interests, and presents a user-user collaborative filtering system solely based on this implicit feedback data. Paper [42] contributes with an approach to respond to rapidly changing data and the ability to infer skill sets and expertise from performance and not only from worker profiles.

Hybrid Approaches are basically the combination of more than one method together to achieve better results. Papers [39,78] present a number of ways to combine two or more recommendation techniques, as summarized in Table 4. The approaches to integrate vary from combining separate recommenders, adding characteristics of one model into another, or developing a single unified recommendation model.

Mixing CBR and CF approaches occurs in [36], where the authors proposed a two-step process to calculate a score to candidates matching simultaneously the information extracted from the resumé (CBR) and other job applications (CF). In [71], the authors mix CBR and KNN techniques to make recommendations. There is no limitation of the number of techniques and how they are combined. For instance, in [35] a hybrid infor-

Table 5 Overview of the two major areas containing other methods for eRRS

Underlying method	Description
Artificial and Deep Neural Networks (ANN + DNN)	ANN are computational methods developed with inspiration on how the brain functions and evolved over the decades as powerful solution techniques for a number of complex tasks. More recently, neural networks with deep layers have been devised increasing even more the computing capabilities of ANN. DNNs are now considered the state of the art for solving a number of problems, and have also been applied to eRRSs [11,14,51,67,80]
Artificial Intelligence and Machine-Learning (AI+ML)	Artificial Intelligence is the umbrella term used to refer to those computational techniques that *learn* to solve problems instead of being programmed to do so. Machine-Learning are those AI methods that deal with learning from data. Both have been used in the context of eRRSs in a variety of ways [15,17,25,31,43,62,63,69,74,77,87,89,91–93,95]

mation filtering engine encompasses several recommendation engines: demographic-based; knowledge-based, content-based, concept-based, ontology-based integrated with behavior and collaborative-based recommenders segregated on different but integrated modules; or in [96] where it is presented an ensemble method for job recommendation to the ACM RecSys Challenge 2016[1] described as a solution which is an ensemble of two filters, combining the merits of traditional collaborative filtering and content-based filtering. Several methods developed for the same challenge are presented in [18,47,48,52], in which ensembles interaction with content data. In [37] the authors make recommendations based on social endorsed skills. An interesting paper [66] proposes to segment users according to the willingness of a new job and applies a specific recommendation method to each one. In [20,38] it is contrasted different methods on a dataset to check which performs better, or uses them together to overcome their particular deficiencies.

Knowledge-Based Recommenders (KBR) expand the matching capabilities using some domain expertise identifying similarities over contexts [61] instead of terms. In [16] it was proposed a CBR to recommend users with job offers that better suit their profile and learned preferences, and the best offers presented rely on the semantic vocabulary of the job offers corpus and user's profile gathered from his resumé. The study [26] proposes an ontology for IT jobs. In [24], the authors use data from LinkedIn users' public profiles in an attempt to find out relationships between jobs and people skills using Latent Semantic Analysis (LSA) to generate semantic associations. And, finally, in [81] it is analyzed the implementation of an ontology-based recommender system that offers suitable jobs to disabled people. Ontologies, such as WordNet and Yago3, are used commonly. In [44,45,60] the authors use them to link concepts by several types of semantic relations.

Other Techniques include a group of non-traditional approaches aiming to solve the job recommendation problem by extending traditional recommender systems. In a nutshell, these methods can be divided into two broad areas: Artificial and Deep Neural Networks (ANN+DNN); and Artificial Intelligence and Machine Learning (AI+ML), as summarized in Table 5. It is important to note, however, that some papers based on AI, ML, ANN and DNN may also fit well in some of the previous categories. Whenever this happened, these were placed in the previous categories, and we maintained here only the works that provided stronger emphasis on their AI, ML or NN approach.

[1] http://2016.recsyschallenge.com/.

In the past years, Artificial and Deep Neural Networks have been used in e-Recruitment Recommender Systems. In [11] the authors organize the job applicant clickstreams history on various job boards as time series and then apply a DNN to predict future values of the clicks on job boards. In [14] a hybrid approach is proposed mixing content and collaborative data enriched with Deep Learning to address the cold-start and sparsity problems. In [15], it is proposed an online mining and predicting system for personalized job or candidate recommendation. Three types of information networks were created in [17] based on past jobs' information: (a) job transition network; (b) job-skill network; and (c) skill co-occurrence network. The model uses information from all three and learns, through representational learning, the representation of the jobs and skills in a common k-dimensional latent space. Another use of DNN to harness the cold-start problem is presented in [80], which employs a form of multi-edge graph linking jobs' similarity by several attributes. In [51,67] the solutions employ the Long Short-Term Memory (LSTM) deep network, which is a well-known recurrent neural architecture within DNNs. The former work combines temporal learning with sequence modeling and the latter divided the recommendation problem into sub-tasks, also dealing with the cold-start problem.

In [25] it is tackled the problem of recommendation on high volumes of data introducing a Monte Carlo Tree Search to reduce the computing load. It is proposed a form of contextual grouping of similar candidates and jobs to avoid the search over the whole vector space. Paper [31] proposed a rule-based data mining technique to make job recommendations on the basis of matching the candidate's profile while preserving the candidate's job behavior or preferences. In [62] the authors applied Random Forests and Support Vector Machines to determine whether a job offer is relevant or not for a specific candidate. Other approaches that explicitly use Machine Learning algorithms to perform e-recruitment recommendation are the works of [43], which employ an Expectation–Minimization (EM) algorithm to cluster users, and [69] which pre-select job offers based on a Gradient Boosting Decision Tree. Finally, in [87] the authors implemented a real-time AI system with a question generation algorithm to simulate an interview environment for the preliminary rounds of recruitment. In [89] it was proposed a reciprocal recommendation model based on bi-directional preferences in a people-to-people recommender system. In [77] it is presented a case-based Multi-Agent System (MAS) which integrates an ontology to select and recommend job seekers to the recruiter or vice versa. Additionally, in [74] the author mix a CBR approach with a multi-agent argumentation framework, which adapts the match by giving more importance to some features than to others. As an extensive feature engineering is required to construct and keep the user profile up to date, novel methods have been researched, like in [95], where it is suggested the use of Statistical Relational Learning, which provides a straightforward way to combine approaches and directly represent the probabilistic dependencies among attributes.

B. Information usage and its origin

The core of an e-recruitment recommender system includes the candidate and the company's interest; that is, which type of job vacancy is of interest and suitable to the candidate, and which type of candidate is interesting and suitable for the company. The way eRRSs have to find an adequate match between these two parties is by gathering information about them. There are basically two broad types of information for job recommendation [73]: implicit and explicit. Explicit information is the one consciously entered by the candidate (company), such as the desired job type (candidate profile), desired location and experience required.

Table 6 List of selected papers categorized by year and information type

Source/year	SN	R&JP	B&F	Other
2012	[27,29]			
2013	[22,36]			
2014	[23,28,34]	[31,57,61]		[91]
2015		[16,44,45,56,77,90]		[92]
2016	[24,47,51,52,63,71,96]	[9,26,42,65,66,93]	[53,89]	
2017	[25,48,69,94,95]	[18,54]	[11,14,73,80]	
2018	[15,85]	[10,17,35,41,62]		
2019	[37,64,74]	[8,20,38,60,98]	[43,67]	[81]
2020				[87]

SN social networks, *R&JP* resumés and job posts, *B&F* behavior or feedback, Others

Implicit information is the one inferred while the candidate interacts with the system, such as candidate–job interactions (e.g., page visits, clicks, reads, job posts' saved, etc.).

Recommender systems can use a variety of information sources to perform recommendation. In the context of e-recruitment, data can be extracted from social networks, resumés, job posts, users' behaviors and/or feedback, skills, questionnaires, geolocation, demographic, and others. In the present review, we categorize the sources of information used to perform recommendation as follows:

- *Social Networks (SN)* social media sites, like Facebook, LinkedIn and XING (a professional social network site born in Hamburg, Germany in 2003), enable users to create and share content, including their profiles, in online environments. The range of information comprehends all features available on the users' profiles, their connections and interactivity records, and their behavior regarding interests and recommended items;
- *Resumés and Job Posts (R&JP)* these are the traditional and explicit sources of information used for the matching process between job vacancies and candidates. Despite its conceptual simplicity, information matching may require the use of ontologies or some sort of knowledge organization to improve the result;
- *Behavior or Feedback (B&F)* these comprehend the actions of the users before or after recommendations are made. Behavior is basically an implicit type of information, mainly candidate-job interactions (e.g., clicks in job posts, time spent reading a certain job description, job posts saved for later review, etc.);
- *Others* a number of other types of information can be used as input for eRRSs, such as skills, questionnaires, demographic data, geolocation, etc.

The different types of information exert an influence on the underlying recommendation method. Table 6 organizes the selected papers by year and the types of information used.

Social Networks (SN), mainly the professionals ones like LinkedIn and XING, are becoming important sources of information for recruiters. It is easy to note that professional profiles turn to be even more relevant than resumés, like in the work of [29], which captures candidates objective information from LinkedIn and also scans on the candidate's online footsteps to infer his/her personality. In [28] information from resumés is also employed and taxonomies [27] are created as hierarchical terms with a correlated semantic meaning. In [22,28,64], the authors use information from Facebook or other social media, together with LinkedIn, to capture professional skills together with interactions and connections from candidates, presenting a form of estimating the importance of each field of users and jobs to generate a recommendation.

In addition to the previously cited papers, the other works that use social network data to perform e-recruitment recommendation are listed in the first column of Table 6. Here, there is one particular case that deserves attention. The annual ACM Conference on Recommender Systems (RecSys) features the presentation of research results, systems and techniques in the broad field of recommender systems. Every year RecSys promotes a challenge based on a real-world task involving RS. In 2016, the selected topic for the RecSys challenge was Job Recommendation, co-organized by the social network XING, and which aimed to predict the job postings that were more likely to be relevant to the user. The competition made available various data sources, and the goal was, given a XING user, to predict those job posting that a user would interact (e.g., click or bookmark) with. The reviewed works that either proposed solutions to the challenge or used its data to evaluate eRRSs proposals are [47,48,51,52,63,69,71,93,94,96].

In principle, recommender systems use the job posts provided by the contracting company and the professional data of the candidates available in their resumés to make the recommendation. Data from candidates include resumés' fields like gender, age, job intention, salary range, area of expertise, and text information such as educational background and work experience. Job posts' data include job description, minimum requirements, salary range, welfare, and so on. A number of works in the literature use such data, as summarized in the second column of Table 6. The job offers can be categorized using a bottom-up approach, as proposed in [56], where common terms are added to descriptions based on their classification, improving the matches with resumés. Some papers, like [44,45,60], present ways to structure the data extracted from resumés and job posts' documents, transforming them into relevant and comparable information. Others contribute to select the best set of attributes (features) to be employed during the match, as proposed in [57].

The remaining works are divided into two minor classes, those that use behavior or feedback type of information ([11,14,43,53,67,73,80,89]) and those that use other kinds of information, such as skills and questionnaires ([81,87,91,92]). Figure 2 summarizes the distribution of the reviewed papers within the four types of information used.

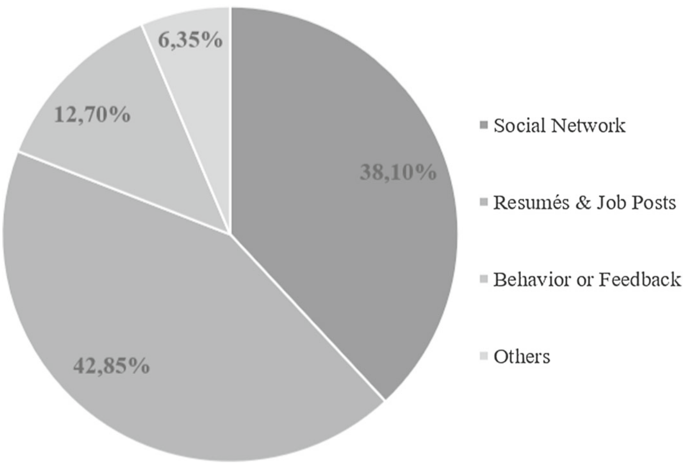


Fig. 2 Usage of information

C. Assessment methods

Recommender systems usually produce a *score*, generally known as *utility*, for items to be chosen, or a list of the N most recommended items or with the highest score. Assessing the performance of a recommender system is an inherently non-trivial task, and the main reason for this is the subjectivity of the recommendation: an item that I may find very interesting can be very uninteresting to another user, even if the other user has some preferences similar to mine. When the recommendation considers historical data for one or more users, different distance measures between the predicted utility of an item and a known utility value of a test set can serve as a performance estimate. In cases where such historical information is not available, the performance of the system usually follows that used by Information Retrieval systems, such as Precision, Recall and F-measure. In our survey, we will divide the eRRSs evaluation measures into four broad categories:

- *Expert Validation (EV)* comprehends all sorts of validation against another form. It can be a manual validation, when the comparison is made by the recommendation picked manually by an expert, or automatic, when the results are compared with another state-of-art technique.
- *Machine Learning (ML)* metrics used to measure the quality of the artificial intelligence or machine learning model, such as predictive measures, like the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Standardized Mean Error (SME), and set recommendation measures, like Precision, Recall, F-measure, Area Under the Curve (AUC), and the ROC curve.
- *Challenge Metrics (CML)* are essentially ML Metrics tailored to assess a recommender system targeted at a specific challenge. An example of this is the metric devised by the RecSys 2016 challenge that took into account Precision, Recall and User Success, all in a single metric.
- *Utility* is the standard terminology of a recommender system metric, but we used it here to refer to all other metrics that did not fall into the previous categories, such as click-through rates (CTR) and expression of interest (EOI).

The evaluation methods are summarized in Table 7 following the four categories proposed here. Although performance assessment in central in any learning approach, note that not all studies papers reviewed provide a clear form to validate the results.

Table 7 List of selected papers categorized by year and assessment method

Source/year	EV	ML	CML	Utility
2012	[27,29]			
2013		[22]		
2014	[28]	[23,34,57,61]		
2015		[44,45,56]		[77]
2016	[9,42]	[24,66]	[47,51,52,63,69,71,93,96]	
2017	[11,25]	[14,18,95]	[48,94]	[54,80]
2018	[10,17,62]	[41]	[15]	[85]
2019		[20,37,43,60,67]		[74,81,98]
2020				

EV expert validation, *ML* machine learning metric, *CML* challenge metric, Utility

5 Final remarks

In this concluding section we are going to provide a general overview of our systematic review findings, and then summarize to the reader the current trends and open research problems of e-recruitment recommenders.

A. Overview of the survey

This work is the first systematic literature review of e-recruitment recommender systems. It was written in order to shed light into three key questions concerning eRRSs: which type of recommender system is being used; what kind of information is used to perform the recommendation; and how the eRRS is assessed. Altogether, the answers to these questions allow a minimal design for a successful e-recruitment recommender.

Concerning the first research question, we initially adopted the standard recommendation type nomenclature into content-based (CBR), collaborative filtering (CF), knowledge-based (KBR) and hybrid, but added another category called *other types* (OT), which included AI or machine-learning, or artificial neural networks and deep neural networks as subcategories. The latter allowed us to identify some novel forms of devising recommender systems in addition to the standard ones. Our survey showed that 26.98% of the works were of the CBR type, 20.63% were Hybrid, 33.33% were of other types, and only 6.35% were predominantly of a pure collaborative-filtering approach.

In terms of the information used to draw recommendations, data from resumés and job posts are still the most used ones (42.85%), but information extracted from social network sites has gained a lot of attention over the past years and appears in second in this ranking with 38.10% of the works using it exclusively or in combination with other data. Then, user behavior and/or feedback is predominantly employed in 12.70% of the works reviewed, and other types of info, like skills, questionnaires and geolocation, appeared in 6.35% of the papers.

Finally, considering the assessment measures, machine-learning metrics, such as Precision, Recall, AUC, ROC curve and F-measure, are still the predominant ones, appearing in 41.67% of the papers. A large number of works were also published within this period using challenge datasets, more specifically the RecSys 2016 challenge dataset, composed of professional social network data. This assessment method amounted to 22.92% of the papers reviewed. The use of expert validation or comparison with other approaches covered 20.83% of the works, and other utility measures were responsible for 14.58% of the literature.

B. Current trends and research challenges

Despite our crisp categorization, there is notably a trend for hybrid works and non-traditional techniques to extent the recommender capabilities. Current traditional approaches alone have some benefits and may partially satisfy the need to bring candidates closer to vacancies. However, when applied in isolation they may fail in at least one respect and there is no way to fully meet the requirements alone. Therefore, instead of a single model, a set of recommendation engines, acting in parallel, each establishing a ranking of items to recommend tend to deliver better results. This set of rankings may, by the presence of a certain item on more than one list, corroborate the relevance of a recommendation. This set of algorithms can be customized for each user, where a specific weight is assigned, and thus the final recommendation suits each contextual preference. Furthermore, it is crucial to capture user behavior while interacting with the system, causing it to receive these implicit feedbacks and adjust accordingly.

Besides the recommendation's utility, a minority of the papers focused on business metrics. For instance, (a) how faster and at what quantity candidates are applying for job opportunities because of recommendations; (b) what is the percentage of good candidates recommended over all recommendations; (c) the interest of candidates and recruiters are balanced, if not, what is the root cause. Regarding this last issue, it is possible to infer that some positions are harder to fulfill than others and, maybe, there is something wrong with the job description or there is another unrealistic requirement that is blocking candidates to get attracted.

Nevertheless, defining these metrics do not suffice the challenges to evaluate the system. The concept of relevance of a recommendation is volatile, and the hiring process has a short duration. From the candidate's perspective, there is no point to recommend a job after the hiring process is already finished. The same holds true from the recruiter's perspective. Thus, evaluating the recommendations depends on collecting feedbacks along several users and for a considered time frame. Another challenge is regarding the candidate's willingness for a new job. Even if a potential matching candidate gets aware about the opportunity recommended but do not demonstrate interest, the system cannot differentiate the reasons of his indifference, unless informed. So, this recommendation is relevant or not? In such cases, the candidate can let the system know that this is a good recommendation, but it is not an appropriate time for him to make a move on his career. Or, the recruiter himself can let the system know the fact over that candidate, marking him as a good potential fit candidate, despite the lack of his interest, and the system was right to recommend him over other candidates. This is vastly different from irrelevant recommendations and should be treated differently to avoid biases. It is also important to stress that eRRS are not as easy to evaluate and therefore require a notable feature engineering to get the right diagnostic.

Finally, eRRS remains an open field of research with great economic interest. The adoption of automated practices in recruitment and selection processes still represents a small fraction over hires performed worldwide and will become the mainstream approach in a near future.

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