

# Evaluating Recommender Systems for Technology Enhanced Learning: A Quantitative Survey

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**Abstract**—The increasing number of publications on recommender systems for Technology Enhanced Learning (TEL) evidence a growing interest in their development and deployment. In order to support learning, recommender systems for TEL need to consider specific requirements, which differ from the requirements for recommender systems in other domains like e-commerce. Consequently, these particular requirements motivate the incorporation of specific goals and methods in the evaluation process for TEL recommender systems. In this article, the diverse evaluation methods that have been applied to evaluate TEL recommender systems are investigated. A total of 235 articles are selected from major conferences, workshops, journals, and books where relevant work have been published between 2000 and 2014. These articles are quantitatively analysed and classified according to the following criteria: type of evaluation methodology, subject of evaluation, and effects measured by the evaluation. Results from the survey suggest that there is a growing awareness in the research community of the necessity for more elaborate evaluations. At the same time, there is still substantial potential for further improvements. This survey highlights trends and discusses strengths and shortcomings of the evaluation of TEL recommender systems thus far, thereby aiming to stimulate researchers to contemplate novel evaluation approaches.

**Index Terms**—Recommender systems, evaluation, survey, technology enhanced learning

## 1 INTRODUCTION

RECOMMENDER systems play an increasingly significant role in Technology Enhanced Learning (TEL). With this growing importance comes a corresponding need to perform comprehensive evaluations. Often, methods applied to evaluate recommender systems in other domains such as e-commerce are reused in TEL [1]. Recommender systems for TEL have unique requirements as their goal is to support the learning process [1], [2]. Therefore, the adequate evaluation of recommender systems for TEL demands specific methods. As a result, there is a need to investigate these particular requirements for TEL recommender systems and how they can best be evaluated. Manouselis et al. [1] notice the similarity of recommender systems for TEL with *Adaptive Educational Hypermedia* systems. They conclude that the evaluation requirements for these systems can be adopted to the evaluation of TEL recommender systems, complementary to recommender specific aspects.

A discussion of evaluation methods can be found in [3] and in [4]. The evaluation of TEL recommender systems has been considered as one variable of analysis in two surveys: [5] and [6]. Both show that in many cases, research works do not fulfill expectations for a valuable evaluation. This

survey offers a representative and detailed quantitative analysis of research on TEL recommender systems, focusing specifically on their evaluation. In Section 2, the TEL specific requirements for recommender systems are analysed. In Section 3, the evaluation goals and evaluation methodologies for evaluating TEL recommender systems are presented, as well as the challenges facing the evaluation of TEL recommender systems. In Section 4, the approach used for the literature survey is described and the classification criteria are introduced. Results from the survey are summarized in Section 5. Finally, this paper concludes in Section 6 with an overall discussion of the trends analysed in the survey and an outlook on future challenges facing the evaluation of TEL recommender systems.

## 2 REQUIREMENTS OF RECOMMENDER SYSTEMS FOR TEL

Due to the ever increasing amount of information found on the web, it becomes more and more difficult for learners to find suitable items to satisfy a particular need. Recommender systems aim to reduce this burden of information overload by predicting relevant items of interest to a user. A recommender system is basically made up of a recommendation engine that creates a recommendation list of items, sorted by their relevance to a particular information need. In order to provide personalized recommendations, which are recommendations tailored to a certain person, the user's context and the user's profile (e.g. user preferences, transaction history, demographics) need to be considered when generating recommendations. There are different kinds of recommender systems. The main types can be classified as:

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content-based, collaborative filtering, knowledge-based, and hybrid recommender systems [7]. Collaborative filtering approaches use community data such as feedback, ratings, tags or clicks from other users to make recommendations. Content-based approaches make recommendations using content features to identify similar items or determine the similarity between items and the user's profile. Knowledge-based approaches utilize knowledge bases and knowledge models (e.g. ontologies) to generate recommendations. Hybrids combine several of these approaches thereby exploiting their advantages and avoiding their limitations. A comprehensive survey of the state-of-the-art recommender systems can be found in [8].

## 2.1 Recommender Systems for TEL

Technology enhanced learning is a broad field ranging from formal to informal learning, from classroom to workplace and mobile learning, and covers almost all topics in our everyday lives. As technology is used in different learning scenarios, so also have recommender systems been used to support different learning scenarios. The main aim of recommender systems in TEL can be summarized as supporting learners during their learning process in order to accomplish their learning goals [9], [10]. A recent survey of TEL recommender systems can be found in [9] and an overview of research trends and applications of recommender systems for TEL in [11]. Additionally, a survey of context-aware TEL recommender systems can be found in [5].

Recommender Systems for TEL recommend a wide variety of items such as learning objects, learning resources on the Web, software, foreign language lessons, test items, lecture notes, or complete courses [2]. The recommender systems identified in this survey make very diverse recommendations, including learning resources, fellow peers, and more TEL specific items such as learning sequences, advice to teachers or grade predictions. These findings are not surprising and confirm those reported in related work [9].

## 2.2 Requirements of TEL Recommender Systems

Personalized recommender systems are applicable to a TEL scenario as their characteristics can be mapped to corresponding principles in the learning sciences that are needed to facilitate learning [2]. These particularities lead to new requirements for recommender systems for TEL as compared to other domains [1].

The first requirement is to reflect the individual learners needs. These needs depend on different characteristics of the learner. A very important aspect is the individual knowledge or competence level [2], [12]. An item recommended at a certain point in time could be too easy or too difficult to a learner depending on the learner's level of ability [13]. For example, an expert needs different recommendations than a novice. One aspect which should be taken into account is, that knowledge levels change over time [2]. Learners never reach a final knowledge level or competency state, but instead move on to attain the next level of knowledge or competency [10], [12]. Other aspects to be considered are the changing interests or learning activities of a

learner. In addition, there are more or less stable characteristics, such as learning styles, which should also be taken into account [2].

The second requirement is based on pedagogical theories. Learners should be confronted and challenged with unexpected content as this would encourage the learner to learn through discovery and exploration. Recommending items that are different to those a learner already knows could stimulate critical thinking and counter confirmation biases [2]. Recommender systems for TEL should thus recommend novel [3], diverse and serendipitous learning resources [2]. For example by providing preference-inconsistent recommendations [14].

It therefore becomes increasingly important to evaluate recommender systems with respect to these particularities and requirements.

## 3 EVALUATING RECOMMENDER SYSTEMS FOR TEL

Evaluation experiments are conducted in order to assess how well a recommender system fits specified requirements (such as those mentioned in Section 2). These requirements thus lead to the evaluation goals or the effects to be measured by the experiment.

### 3.1 Evaluation Goals

The goal of an evaluation is to measure a certain property or effect of the recommender system. In [15], Shani and Gunawardana present a selection of several properties from different domain areas that could be measured by an evaluation. Also in [12], Drachsler et al. introduce several parameters and differentiate between technical and educational parameters. Inspired by these properties and the requirements discussed in Section 2, in the following, we present three broad categories of evaluation goals for TEL recommender systems.

#### 3.1.1 Measuring Recommender System Performance

System performance evaluation goals aim to measure the performance of the recommender system or recommender algorithm from a technical point of view, such as the prediction accuracy, the recall and coverage of the algorithm and the relevance of the recommendations [15]. Another technical measure is the execution time or prediction speed of a recommender algorithm in generating recommendations [12].

#### 3.1.2 Measuring User-Centric Effects

User-centric evaluation goals aim to measure the general perception of the recommender system by the user. This includes the user's preference for or satisfaction with a system, the user's trust in the recommendations from the system, the user's perceived novelty, diversity and serendipity of the recommendations [15]. Other user-centric properties are for example user experience and expectations [16], user satisfaction [16] and the perceived usefulness of explanations of recommendations [17]. Another aspect is how well a recommender system supports the user in achieving a specific task or goal [3].

### 3.1.3 Measuring Effects on Learning

Educational measures or learner-specific evaluation goals aim to measure specific properties related to learning, thereby encompassing the TEL requirements from Section 2.1 and supplementing the properties presented in [15]. This is in accordance to [6], [12], where effects on learning are also differentiated from the recommender algorithm's performance. One of such goals is to measure the learning performance of the learner. This comprises measuring the learner's individual knowledge or expertise level on a particular topic and comparing the learner's learning achievements and scores in tests. Learning effectiveness is another goal with the aim to measure the number of visited, studied or completed items during a learning phase. A further goal is measuring the learner's achievement efficiency, which indicates the time needed by a learner to reach a learning goal [12]. Another goal is measuring how the system affects the learning motivation of the learner [18].

## 3.2 Evaluation Methodologies

The methodologies for the evaluation of TEL recommender systems can be classified into three types according to [3] and [15]: offline experiments, user studies and real life testing. Each evaluation methodology has its advantages and disadvantages [19], [20] and may be better suited to evaluate certain goals than others.

### 3.2.1 Offline Experiments

Offline experiments (also called *dataset driven evaluation* [21]) use datasets consisting of user interactions to evaluate recommender systems. Two kinds of datasets are often used: (i) Natural or historical datasets consisting of historical interaction data of real users in a real system over a period of time. Explicit user ratings can be collected or implicit user feedback extracted from user log data. (ii) Synthetic datasets are artificially constructed datasets usually used to test how recommender algorithms perform in constructed scenarios and under specified conditions. Parameters such as the distribution of user properties, the size or rating sparsity [7] can be pre-defined in order to create datasets fulfilling certain criteria. Offline experiments simulate the recommendation process where items are given to a user and the user acts on this by giving feedback like tagging, rating or buying the item [15]. Thereby, a subset of the user's interactions in the dataset are hidden or withheld and the recommender system has the task to predict these hidden interactions. The recommender system is evaluated according to how good it can predict these hidden interactions. Such a simulation can be conducted using cross-validation [22] or time-stamps [15]. For cross-validation, the given dataset is split into two parts: the training set which is used to train the recommender algorithm or to generate the recommendation results and the test set used to validate the performance of the recommender algorithm [22]. In datasets where time-stamps are available, time can be used to simulate how recommendations could have been made at the time the system was running. This is done for example, by starting at the earliest time-stamp in the dataset and stepping through in temporal order, thereby hiding the user's future interactions which the recommender system

attempts to predict [15]. A detailed list of TEL datasets can be found in [21] and in [23], as well as a survey of linked-data datasets, available social data and data formats in [24].

### 3.2.2 User Studies

A user study is a scientific method used to find out how a recommender system influences a user's experience, perception and interactions with a system [25]. User studies are typically performed in the human sciences [26]. User studies cover a wide range of evaluation questions [15], however these are very subjective judgements. A user experiment is usually executed by asking users to perform some tasks in a controlled environment for a short period of time. The interaction behaviour of the users with the recommender system is observed and recorded. For example, the time taken to complete a task or the quality of the results of a task. Users are often asked questions before, during and/ or after the experiment. Such questions, often prepared as a questionnaire or asked in an interview, help to capture aspects that cannot be directly observed otherwise, such as how the user feels about using the system or taking part in the experiment. Participants in a user study should generally be unbiased users of the system and need to be selected randomly from a representative population sample [15]. The sample size should be large enough to achieve statistically significant results [25].

### 3.2.3 Real Life Testing

In real life testing, also known as online evaluation [15], real users use the system under normal conditions over a long period of time [3]. This might be as a field study where a large community of users is observed while using the system under realistic conditions or as a pilot study where a system is deployed in its real life setting. With real life testing, most user-centric goals can be effectively evaluated such as measuring user experience or user satisfaction [19].

## 3.3 Challenges of Evaluating Recommender Systems for TEL

The evaluation of TEL recommender systems faces several challenges as reported in [3]. Thus there is an increasing need to review the evaluation of TEL recommender systems in order to discuss new ways forward. These challenges motivate this survey.

### 3.3.1 Availability and Limitations of TEL Datasets

In contrast to the other evaluation methodologies, offline experiments are fast and require a low effort to conduct. They are usually executed in several hours depending on the size of the dataset and speed of the algorithm. Offline experiments are however limited to the historical interactions recorded in the datasets. Items in the dataset that were not *interacted* with in the history of a learner are considered not interesting nor relevant to the learner, this however might not be true [16]. Furthermore, offline experiments are limited by the fact that TEL datasets fulfilling all necessary requirements for the evaluation of a specific type of recommender algorithm are not always available e.g. for evaluating multi-criteria recommender systems [27]. Synthetic

datasets can be used in the initial development phases (when no real data yet exists) to help decide on certain choices or settings or tuning models [19]. The evaluation results however need to be verified with real data later on [28].

### 3.3.2 Necessity for User-Centric Evaluation for TEL

User-centric evaluation focuses on the perceptions of the user and not on the technical performance of the recommender system. User-centric measures such as usability or user satisfaction are best evaluated by asking the users themselves [16]. Although some attempts have been made to measure such effects in offline experiments, measuring effects like the user's trust in a system is just not possible with an offline experiment [15]. Measuring effects on learning are also typically done using user-centric evaluation [6]. Therefore and in particular for TEL, user-centric evaluations are crucial but they unfortunately remain expensive to conduct.

### 3.3.3 Limited Availability of Participants for User Studies

Finding a sufficient number of willing participants for user studies is a challenge. User studies usually require several days to conduct as it is not always possible to get all participants to take part in the study on the same day. Additionally, there may be constraints on the availability of resources (e.g. rooms, PCs or licenses). For user studies, if several variations of an experiment need to be evaluated, then the participants have to be shared out across the different treatment conditions, thus further reducing the number of participants per variation. If the same participants should evaluate several variations, then other issues arise, such as user bias as the participants gain more knowledge about the system [15].

### 3.3.4 Limitations of Real Life Testing

Real life testing is particularly challenging for TEL and requires a lot of effort as real learners need to use a mature system earnestly for a long period of time under real conditions. Deploying and maintaining a system in a real life setting is expensive as it requires sufficient resources such as enough computational capacity, adequate user support or even user training. For real life testing, it is nearly impossible to have many variations of a system evaluated. A possibility to still accomplish this, is to switch algorithms or user interfaces during testing. This however limits the amount of time available to test a single variation of the system [15]. Additionally, real life testing has the same problem as user studies but even amplified, as the participants over time get to know the system and any changes would be noticed and eventually affect the evaluation results [16]. Moreover, there is a high risk to real life testing as users are easily frustrated and could abort the evaluation when the system's performance is lower than expected [15].

### 3.3.5 Comparability of Evaluation Results

Unlike in other domains, there are no standard datasets nor standard evaluation procedures for evaluating TEL recommender systems [12]. This limits the comparison of evaluation results between TEL recommender systems. Evaluation

frameworks exist to support offline experiments on datasets, for example for the evaluation of folksonomy-based recommender systems [29] or for the simulation of multi-criteria recommender systems [30], but these solutions have very narrow usage scenarios. Several user evaluation frameworks have been proposed to guide the design and execution of user experiments to evaluate recommender systems [17], [31], [32], however once again, due to the high cost of conducting user studies in TEL, these frameworks have not been extensively implemented nor comprehensively adapted to fit TEL requirements. Recently, this open challenge has been addressed and a user centred evaluation approach has been proposed and explored extensively [6], [33].

## 4 AN ANALYSIS OF LITERATURE ON EVALUATION OF RECOMMENDER SYSTEMS FOR TEL

In several surveys, amongst other aspects, the evaluation of TEL recommender systems has been repeatedly investigated. In [3], 42 TEL recommender systems were reviewed in respect to how they were evaluated, reporting on the status of the system, the evaluator focus and the evaluation roles. Similarly in [6], 59 TEL recommender systems were reviewed stating what the evaluation focus was and what the evaluation roles were. These surveys however did not aim to give an overview of how the evaluation of TEL recommender systems has evolved over the years. Neither were further details reported regarding the particular evaluation method applied, the exact number of participants in the experiments, nor the effects measured. Furthermore, in [5] only context-aware recommender systems were considered. A qualitative analysis of the existing systems was carried out and only 13 systems were categorized regarding the effects measured by the evaluation.

In contrast, in this survey, a total of 235 publications have been systematically selected as being relevant to recommender systems in TEL and a quantitative analysis of the results of the survey is presented in detail in tables or visualized as plots. Thereby, a visual analysis of the trends detectable regarding the evaluation of TEL recommender systems between 2000 and 2014 is given. The process of the selection of the 235 publications and the classification criteria used in this survey are explained in the following sections.

### 4.1 Selection of Publications Reviewed in Survey

In this survey, an analysis was conducted of recommender systems related literature published in relevant conferences, workshops, journals and books having a clear focus on educational technology. Overall, publications in the time-frame between January 2000 and December 2014 were considered. However, some venues came into existence later than 2000 and some existed only for a limited number of years. Therefore depending on the venue, the time-frame considered varies. Not all venues had relevant publications for each year and the special issues or specialized workshops only took place in certain years, thus the number of publications per year varies as well. Three journals were analysed, namely Elsevier Computer & Education<sup>1</sup> (2000-2014),

1. <http://www.journals.elsevier.com/computers-and-education>, retrieved 20.05.2015

Journal of Computer Assisted Learning-JCAL<sup>2</sup> (2000-2014) and IEEE Transactions on Learning Technologies-TLT<sup>3</sup> (2008-2014). In addition, several special issues were included: Social Information Retrieval for Technology Enhanced Learning in the Journal of Digital Information (2009),<sup>4</sup> Special Issue on Recommender Systems to Support the Dynamics of Virtual Learning Communities in International Journal of Web Based Communities (2012),<sup>5</sup> Special Issue on Recommender systems for and in social and online learning environments in Expert Systems (2013),<sup>6</sup> as well as two books: Educational Recommender Systems and Technologies: Practices and Challenges (2012)<sup>7</sup> and Recommender Systems for Technology Enhanced Learning: Research Trends and Applications (2014).<sup>8</sup>

Furthermore, three series of conferences were investigated; two in the educational technology area, namely IEEE International Conference on Advanced Learning Technologies-ICALT<sup>9</sup> (2001-2014), and European Conference on Technology Enhanced Learning-EC-TEL<sup>10</sup> (2006-2014); as well as one leading conference on recommender systems, namely ACM Conference on Recommender Systems-RecSys<sup>11</sup> (2007-2014). A series of specialized workshops were also analysed: Workshop on Recommender Systems for Technology Enhanced Learning-RecSysTEL<sup>12</sup> (2010-2012) and Workshop on Social Information Retrieval for Technology Enhanced Learning Exchange-SIRTEL (2007-2008).<sup>13</sup> Finally, a selection of publications (not yet covered by the aforementioned venues) were included from an existing survey [6] that gives a brief overview of the evaluation of 59 TEL recommender systems.

The selection process for these publications was carried out iteratively. First, a full-text search was conducted to identify potentially relevant publications using the search terms: *suggest*, *recommend*, *recommender*, *recommendation*. For the ACM RecSys conference, which is not a dedicated conference for TEL but rather for recommender systems in general, the search terms used were instead: *learn*, *student*, *education*, *TEL*. Second, the publication titles, keywords and abstracts were perused and candidate publications selected. The classification for the survey was then done manually by reading through the selected publications, thereby focusing on their evaluation. Overall, it was more difficult identifying relevant publications in earlier years as research in TEL recommender systems was not yet fully established and the terms

*recommender system* or *recommendation* were not yet widely used. As a result, fewer publications were found in earlier years and even no publication could be identified in 2001.

## 4.2 Classification Criteria for Survey

Since the requirements of recommender systems are manifold, it is a complex task to evaluate them and many properties have to be taken into account. Besides the performance of the recommender algorithms, the users' perspective also has to be considered [17]. As the goal of this survey is to highlight trends and shortcomings in the evaluation of recommender systems for TEL, a multidimensional classification of the 235 publications selected has been performed. In general, according to Shani and Gunawardana [15], the evaluation of recommender systems can be distinguished by the experimental settings (how is the evaluation conducted?) and the evaluated system's properties (what is evaluated?). Thus in this survey, the focus is also placed on these two criteria. Furthermore, the subject of the evaluation is also considered, since it has an impact on the suitability of the experimental setting. For user studies and real life testing, additional information collected and considered in the analysis were the number of participants in the experiments and the length of the evaluation period, where applicable. In addition, for user studies, the data collection method applied is also analyzed. In contrast to the criteria used in this survey, Santos et al. [6] use three criteria based on a previous survey in [1] to classify the evaluation of recommender systems: who took part in the evaluation (end users, system designers, simulated learners), what the evaluation focus was (algorithm or system), and in the case of an evaluation of the system, they further distinguish between usability, the user's perception of the recommendations and learning performance.

There exist many specific aspects which could be analyzed in such a survey, for example whether specialized methods like layered evaluation is used or whether all levels of Kirkpatrick's evaluation model are regarded in the evaluation, as suggested in [3]. Since the focus of this survey is however a quantitative analysis over time, and only a few of the 235 publications report using sophisticated evaluation methods, additional criteria have not been investigated. The selected publications were reviewed and classified according to the following classification criteria.

### 4.2.1 Type of Evaluation Methodology

The types of evaluation methodologies applied for the evaluation of the recommender system as described in Section 3, are classified into these four categories: *Offline Experiment*, *User Study*, *Real Life Testing* and *No Evaluation*. These categories refer to such as in [3] and in [6].

### 4.2.2 Subject of Evaluation

The evaluation was designed for and applied to either evaluating the entire recommender system or only the recommender algorithm:

- *Recommender algorithm*. Only the recommender algorithm is evaluated. That is, the evaluation focuses only on how well the underlying algorithm predicts or ranks recommendations.

2. [http://onlinelibrary.wiley.com/journal/10.1111/\(ISSN\)1365-2729](http://onlinelibrary.wiley.com/journal/10.1111/(ISSN)1365-2729), retrieved 20.05.2015

3. <http://www.computer.org/web/ilt>, retrieved 20.05.2015

4. <https://journals.tdl.org/jodi/index.php/jodi/issue/view/66>, retrieved 20.05.2015

5. <http://www.inderscience.com/info/inarticletoc.php?jcode=ijwbc&year=2012&vol=8&issue=3>, retrieved 20.05.2015

6. <http://onlinelibrary.wiley.com/doi/10.1111/exsy.v32.2/issuetoc>, retrieved 20.05.2015

7. <http://www.igi-global.com/book/educational-recommender-systems-technologies/55284>, retrieved 20.05.2015

8. <http://www.springer.com/gp/book/9781493905294>, retrieved 20.05.2015

9. <http://ask4research.info/icalt/2015>, retrieved 20.05.2015

10. <http://www.ec-tel.eu>, retrieved 20.05.2015

11. <http://recsys.acm.org>, retrieved 20.05.2015

12. <http://adenu.ia.uned.es/workshops/recsystel2012>, retrieved 20.05.2015

13. <http://ceur-ws.org/Vol-307>, <http://ceur-ws.org/Vol-382>, <http://ceur-ws.org/Vol-535>, retrieved 20.05.2015

TABLE 1  
Evaluation Methodologies

Year	Offline Experiment (75)	User Study (65)	Real Life Testing (30)	No Evaluation (95)
2014 (50)	[42] [43] [44] [45] [46] [47] [48] [49] [50] [51] [52] [53] [54] [55] [56] [57] [58]	[43] [50] [59] [60] [61] [62] [63] [64] [65] [66] [67] [68] [69] [70]	[6] [43] [56] [68] [71]	[24] [34] [35] [70] [72] [73] [74] [75] [76] [77] [78] [79] [80] [81]
2013 (22)	[82] [83] [84] [33] [85] [86] [87]	[82] [33] [86] [87] [88] [89] [90]	[89] [91] [92]	[93] [94] [95] [96] [97]
2012 (46)	[98] [99] [100] [101] [102] [103] [104] [105] [106] [107] [108] [109] [110]	[14] [111] [99] [100] [102] [103] [107] [112] [113] [114] [115]	[98] [107] [116] [117]	[5] [36] [118] [119] [120] [121] [122] [123] [124] [125] [126] [127] [128] [129] [130] [131] [132] [133]
2011 (13)	[134] [135] [136] [137] [138]	[135] [139] [140]	[140] [141]	[142] [143] [144]
2010 (29)	[27] [145] [146] [147] [148] [149] [150] [151] [152] [153] [154]	[148] [152] [153] [155] [156] [157]	[27] [158] [159] [160]	[161] [162] [163] [164] [165] [166] [167] [168]
2009 (26)	[169] [170] [171] [172] [173]	[170] [171] [172] [174] [175] [176] [177] [178] [179] [180] [181]	[182] [183] [184]	[12] [185] [186] [187] [188] [189] [190]
2008 (27)	[191] [192] [193] [194] [195] [196] [197]	[196] [197] [198] [199] [200] [201]	[196] [198] [202]	[38] [39] [203] [204] [205] [206] [207] [208] [209] [210] [211]
2007 (21)	[28] [212] [213] [214] [215] [216] [217] [218] [219]	[220] [221]	[222]	[223] [224] [225] [226] [227] [228] [229] [230] [231]
2006 (13)		[232]	[233] [234]	[37] [235] [236] [237] [238] [239] [240] [241] [242] [243]
2005 (6)	[244]	[245]		[40] [246] [247] [248]
2004 (5)		[249]	[250]	[41] [251] [252]
2003 (3)		[253]	[254]	[255]
2002 (2)				[256] [257]
2000 (2)		[258]	[259]	

- *Recommender system.* Here the focus of the evaluation is on the entire recommender system, including aspects such as the user interface or the system usage, usually as part of a larger learning platform. The recommender algorithm is then not usually explicitly evaluated.

These two categories reflect those used in former surveys, called evaluation focus in [3] and evaluator focus in [6].

#### 4.2.3 Effects Measured by Evaluation

For the classification performed in this survey, the effects measured by the evaluations have been pooled into the three categories introduced in Section 3, since in many publications detailed reports about the individual effects measured are lacking.

##### Performance of Recommender System:

- *Accuracy.* This covers a varied number of effects, all with the general aim of measuring the performance of the recommender system. This includes the prediction accuracy or relevance of the recommendations made, as well as the error rate, recall and coverage of the recommender system.
- *Prediction speed.* The execution time or perceived response time of a recommender system in generating recommendations is measured. This can also be measured as the user's perceived response time of the recommender system at runtime.

##### User-Centric Effects:

- *User satisfaction.* The usability of the system, the learner's satisfaction with the system and the learner's perceived usefulness of the recommendations are measured.

- *Task support.* This comprises different means of support for the current tasks of the learner. Commonly the perceived helpfulness or level of guidance provided by the recommender system are measured.

##### Effects on Learning:

- *Learning performance.* This comprises mainly the perceived effectiveness of learning using the recommender system. Improvements in the learning achievement of the learner are usually measured and the increase in speed with which a learner executes a learning activity.
- *Learning motivation.* The improvement in the level of motivation or engagement of the learner is measured.
- *Correlations.* The correlations between the user activities and measured effects on learning are investigated. Generally, the co-occurrences and correlations between different activities found in the collected dataset are analyzed, for example between the usage logs of a learner and the performance of the learner in an examination.

In the last category, *Other*, all other effects such as emotion, novelty, variety and diversity which are very rarely measured are covered.

## 5 RESULTS OF SURVEY

The 235 selected publications were categorised according to the classification criteria explained in Section 4. The results of the survey are presented and discussed in the following sections.

### 5.1 Type of Evaluation Methodology

Table 1 gives an overview of the 235 publications classified according to type of evaluation methodology: offline

experiments (75 publications—whereby 68 were performed on historical datasets and seven on synthetic datasets), user studies (65), real life testing (30), or as having no evaluation (95). Some short papers did propose evaluation scenarios but then referred to future work for evaluation results, e.g. [34], [35], [36], [37]. Functional testing of prototypes, as performed e.g. in [38], [39], [40] and [41] were not considered as an evaluation of the recommender system.

Some publications covered several evaluation methods, for example, an offline experiment and a complementary user study in [82]. Here the results from an offline experiment evaluating the accuracy of the recommender algorithm are compared with the user satisfaction evaluated in a user study. The findings confirm the claim [17] that for recommender systems, the high accuracy measured by metrics such as precision and recall in offline experiments, does not correlate to a high quality in user experience. This is also an argument in favor of making the distinction between evaluating just the algorithm or the entire recommender system. Another example can be found in [135], where the accuracy of an algorithm is first evaluated in an offline experiment and then two user studies follow to evaluate the user perception and usability of the recommender system. Some evaluations have real life tests followed by user studies or offline experiments. For example, a real life test is conducted in [140] to measure the performance of the recommender system and to generate a dataset, with a subsequent user study with experts to validate the recommendations. In [27], a real life pilot test was run over eight weeks in order to evaluate the teacher's perceived usefulness and quality of the learning resources recommended as well as to collect a multi-attribute dataset for an offline evaluation. Other evaluations conduct a user study and afterwards analyse the data collected, e.g. in [170], two user studies are complemented with a log data analysis, and similarly in [86] and [148] the usage logs collected in a small preliminary user experiment are afterwards analysed in an offline experiment.

The survey shows that the evaluation of TEL recommender systems has become increasingly important over the years. Excluding the years 2000-2005, with a very low number of publications, the number of publications without an evaluation has decreased substantially, from 77 percent in 2006 to 28 percent in 2014. Fig. 1 shows the percentage distribution of evaluation methods over the years. It is also interesting to note that the distribution of the different evaluation methods has remained relatively stable over the last six years with an average of 32 percent offline experiments, 28 percent user studies, 12 percent real life testing, and 28 percent with no evaluation reported.

### 5.1.1 Offline Experiments

The survey revealed that the number of offline experiments remained steady over the years since 2007. Most experiments were executed on historical datasets, for example on MERLOT<sup>14</sup> [44], [46], [108], [146], or MACE<sup>15</sup> [54], [83], [85], [134] and Ariadne<sup>16</sup> [101]. Historical TEL datasets that fulfill

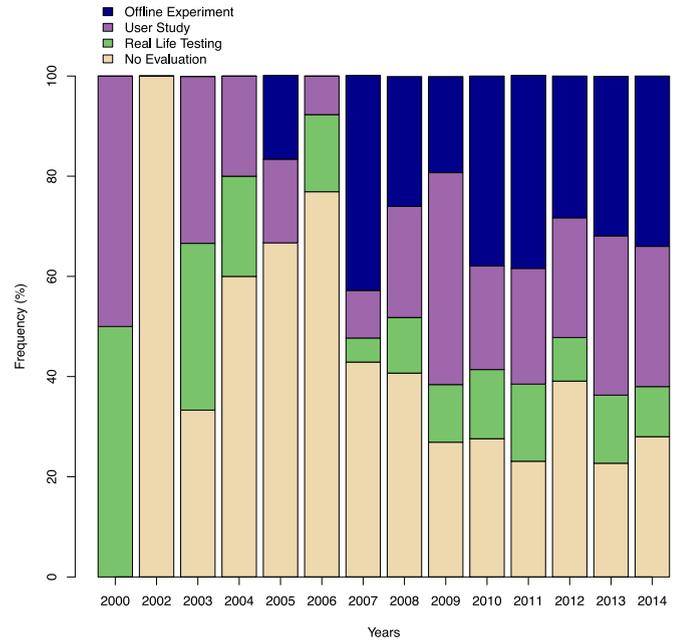


Fig. 1. Evaluation methodologies (percentages per year).

all requirements for an evaluation are however hard to find [27]. An early solution to this problem was to create synthetic datasets and use these for evaluating TEL recommender systems as in [28], [51], [109], [150], [194], [214], [216] and proposed in [208]. Since then, attempts have been made to generate datasets for TEL, for example in [27] where a dataset is generated from a real life testing evaluation. Several offline experiments compared evaluation results to a baseline [49], [54], [56], [58], [83], [106], [147], [171], [212].

### 5.1.2 User Studies

Table 2 gives an overview of methods reported as having been applied in user studies. Questionnaires were used most often. Some studies involved experts, either by giving them questionnaires [139] or by interviewing them [67]. Some did not ask the participants direct questions but rather observed their interaction with the system [67], [89]. Others measured the learner's knowledge before and after an experiment with pre- and post-tests [88]. Fig. 2 shows the distribution of the number of participants in user studies over the years. Each dot depicts a single user study. Only 41 user studies (in 30 publications) reported the actual number of participants. When several user studies are reported in one publication, the individual number of participants per experiment is shown, e.g. in [14] two user studies are performed, one with 121 and the other with 89 participants; and in [253] three studies with 15, 63 and 375 participants. The number of participants ranged between 2 to 375. On average 53 participants took part in a single user study. The median however is 25 as only a few studies had a lot of participants, e.g. 158 in [249]; 159 and 314 in [66]; and 375 in [253]. The mode is 24 in four user studies.

### 5.1.3 Real Life Testing

According to the publications surveyed, real life testing often takes place using a prototype implementation of the

14. <http://www.merlot.org>, retrieved 20.05.2015

15. <http://www.mace-project.eu>, retrieved 20.05.2015

16. <http://www.ariadne-eu.org>, retrieved 20.05.2015

**TABLE 2**  
Methods Applied in User Studies

Year	Questionnaire	Expert's Opinion	Interview	Observation	Tests
2014	[43] [50] [57] [59] [60] [61] [62] [63] [64] [65] [66] [67] [68] [69]	[59] [67]	[67]	[67]	[43] [59] [69]
2013	[82] [86] [87] [88] [89] [90] [91]	[33] [89]	[89]	[89]	[86] [88] [89]
2012	[14] [99] [100] [102] [103] [107] [111] [112] [115]	[107]		[113]	[114]
2011	[135] [139] [140]	[139] [140]			
2010	[155] [157]	[152] [155]		[148] [157]	[153] [156]
2009	[172] [174] [175] [176] [177] [180] [181]	[171]	[177] [178]	[170] [179]	[175] [177]
2008	[196] [198] [199]		[200]	[200]	[197] [198] [201]
2007	[220] [221]	[221]			
2006					[232]
2005	[245]				
2004	[249]				
2003	[253]				
2000			[258]	[258]	

**TABLE 3**  
Real Life Testing Evaluations

Year	Publications	No. of Test Weeks	No. of Participants
2014	[6]	Not stated	173 & 204
	[43]	Not stated	106
	[56]	Not stated	Not stated
	[68]	One Term	153
	[71]	58	34
2013	[89]	58	218
	[91]	1	272
	[92]	8	6
2012	[98]	Not stated	162
	[107]	4	199
	[116]	8	144
	[117]	4 & 16	15 & 36
2011	[140]	8	125
	[141]	16	440
2010	[27]	8	770
	[158]	12	Not stated
	[159]	10	25
	[160]	32	1763
2009	[182]	2 & 4	135 & 160
	[183]	Not stated	Not stated
	[184]	16	244
2008	[196]	58	850
	[198]	4	54
	[202]	Not stated	220
2007	[222]	4 Semesters	104
2006	[233]	Not stated	Not stated
	[234]	2	20
2004	[250]	8	49
2003	[254]	8	54
2000	[259]	36	37

recommender system, sometimes as part of a project deliverable [158], [183]. Publications having a real life testing evaluation are shown in Table 3.

In three publications more than one real life testing scenario was performed [6], [117], [182]. In most real life tests, the whole recommender system was evaluated implicitly including the recommender algorithm. The testing periods lasted about 17 weeks on average and the number of participants were on average higher than for user studies, the

highest count being 1,763 participants over a 32 week period [160] and the lowest six employees who used the system over an eight week period [92]. Some publications stated specific evaluation goals and reported concrete evaluation results such as in [141], whilst in others, the reports on real-life evaluations were very vague, no concrete evaluation results were stated, neither the number of participants, nor the duration of the testing were mentioned [56], [183], [233].

**5.2 Subject of Evaluation**

A distribution of the subject of evaluation across evaluation methodologies is shown in Fig. 3 and over the years in Table 4. As expected, offline experiments are mainly used to evaluate the recommender algorithm (87 percent). This seems to be obvious since in offline experiments, different algorithms or parameters of algorithms can be examined comparatively with a low amount of effort. Contrary to this, in real life testing, the recommender system is normally the focus of the evaluation (77 percent). Interestingly, in user studies, it seems the evaluation focus is nearly as often on the recommender algorithm (49 percent) as it is on the recommender system (51 percent). In some publications, for example in [64], [92], [107], [140], [141], [155] and [212], it was explicitly mentioned that the recommender algorithm was evaluated separately in addition to the overall

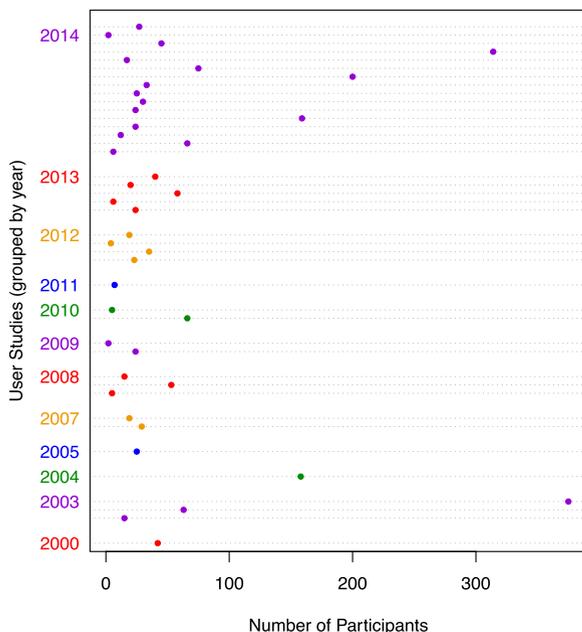


Fig. 2. Number of participants in user studies per year.

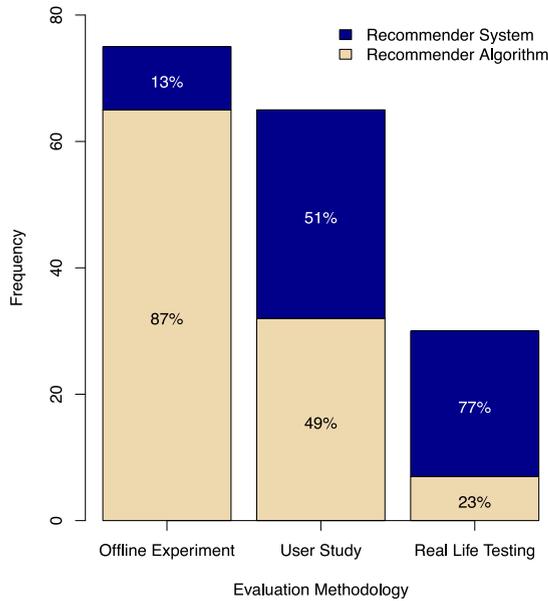


Fig. 3. Subject of Evaluation.

evaluation of the recommender system usually as two distinct phases of the evaluation. In [107] a multi-staged evaluation was conducted where all three evaluation methodologies were covered. In the first stage, an offline experiment (a cross-validation) was executed to measure the accuracy (precision and recall) of the recommender algorithm. In the second stage, a user study (an expert questionnaire) was conducted with four experts evaluating the recommendations with regards to pedagogical aspects. The third stage was a real life testing to evaluate the user satisfaction with the system, here explicit feedback and click behaviour were monitored and log files analysed.

### 5.3 Effects Measured by Evaluation

An overview of the effects measured by the evaluations in the survey are shown in Table 5. One can see that accuracy and user satisfaction are the most common effects measured followed by learning performance, task support, correlations, learning motivation, prediction speed and other rarely measured effects. Fig. 4 shows that in recent years the different types of effects measured have increased and become more varied. Accuracy is measured steadily often from 2007 to 2014, matching the number of offline experiments conducted in these years in Fig. 1. The two user-centric effects, user satisfaction and task support, are measured steadily often over the years. The effects on learning, learning performance and learning motivation, are investigated increasingly often over the years, but only to a relatively small extent compared to the other effects measured such as accuracy. This is certainly due to the corresponding complexity of user studies and especially real life testing.

Fig. 5 shows the effects measured across the evaluation methodologies. User studies and real life testing cover nearly all effects measured. For example, a user study in [64] is performed to measure the accuracy of the recommender algorithm as well as the usability of the whole recommender system. In contrast, offline experiments are mainly used to measure accuracy and prediction speed, but,

TABLE 4  
Subject of Evaluation

Year	Recommender Algorithm	Recommender System
2014	[42] [43] [44] [45] [46] [47] [48] [49] [50] [51] [52] [53] [54] [55] [56] [57] [58] [59] [64] [65] [66] [67] [69]	[6] [43] [56] [59] [60] [62] [61] [63] [64] [67] [68] [69] [71]
2013	[82] [83] [84] [33] [85] [87] [90] [92]	[33] [86] [87] [88] [89] [91] [92]
2012	[100] [101] [102] [103] [104] [105] [106] [107] [108] [109] [110] [115]	[14] [98] [99] [100] [107] [111] [112] [113] [114] [116] [117]
2011	[134] [135] [136] [137] [138] [139] [140] [141]	[140] [141]
2010	[27] [145] [146] [147] [149] [150] [151] [152] [153] [154] [155]	[148] [155] [156] [157] [158] [159] [160]
2009	[169] [170] [171] [172] [173] [174] [181]	[172] [175] [176] [177] [178] [179] [180] [182] [183] [184]
2008	[191] [192] [193] [194] [195] [196] [197]	[196] [197] [198] [199] [200] [201] [202] [260]
2007	[28] [212] [213] [214] [215] [216] [217] [218] [219] [220] [221]	[212] [222]
2006		[232] [233] [234]
2005	[244]	[245]
2004		[249] [250]
2003		[253] [254]
2000		[258] [259]

surprisingly also learning performance. For example, in [151], where a student's performance is measured by a binary state (0 if the student was not able to perform the task correctly and 1 otherwise) and in [104] where the time estimates for the learner to complete a task is taken as an indication of learning performance. Some publications report multiple effects being measured by different evaluation methodologies. For example, in [153], the data collected in a user study, where the learning performance of the participants are measured with pre- and post-tests, is used later to assess the algorithm's accuracy, thereby utilizing so called *good learners' ratings*.

In the following, representative examples from the survey are given, describing how and with which tools and metrics the various effects were measured.

- *Accuracy.* Metrics used to measure accuracy were for example, precision, recall and f-measure in [82] and [83]; Mean Average Error (MAE) in [27] and [83]; and Root-mean-square-error (RMSE) in [136] and [151]. In user studies, for example in [64] and [65], the perceived relevance of the recommendations was measured by asking the users to rate the recommendations received. As measuring the accuracy of a recommender algorithm is not easily decoupled from the impact of the usability of the system as a whole, a usability test was performed as well in [64].
- *Prediction speed.* The prediction speed of the recommender algorithm was measured in [27], [141] and [191].
- *User satisfaction.* The user's satisfaction with the system was measured in [178] and [200], as well as the user's perceived usefulness of the recommendations

TABLE 5  
Effects Measured

Year	Accuracy	Prediction Speed	User Satisfaction	Task Support	Learning Performance	Learning Motivation	Correlations	Other
2014	[43] [44] [46] [47] [48] [49] [50] [51] [52] [53] [54] [55] [56] [57] [58] [62] [63] [64] [66] [69]	[45] [46] [53]	[6] [43] [59] [60] [61] [64] [65] [67] [68] [69]	[6] [43] [59] [62] [65] [68] [71]	[6] [50] [59] [68] [69]	[6] [68] [56]	[42]	[6] [66] [67]
2013	[82] [83] [84] [33] [85] [87] [88] [90] [92]		[82] [87] [88]	[82] [87] [89] [91]	[86] [88] [89] [92]		[85] [86] [89] [91] [92]	
2012	[98] [100] [103] [104] [105] [106] [107] [108] [109] [110] [115] [117]		[98] [99] [100] [102] [103] [107] [111] [112] [117]	[98] [102] [103] [111] [113] [117]	[14] [98] [104] [114] [115] [116]	[98] [116]	[102]	
2011	[135] [136] [137] [138] [139] [140] [141]	[141]	[135] [141]		[141]		[134]	
2010	[27] [145] [146] [147] [149] [151] [152] [153] [154] [155] [156]	[27]	[155] [157]		[151] [153] [156] [158] [159]	[155]	[146] [148] [150] [154] [159] [160]	
2009	[169] [170] [171] [172] [173] [175] [178] [181] [183] [184]		[175] [176] [177] [178] [179] [180] [182] [184]	[170] [172] [177] [182] [184]	[170] [171] [178] [184]	[175]	[170] [174]	[180] [184]
2008	[192] [194] [195] [196] [197] [199] [200]	[193] [191]	[196] [198] [199] [200] [201] [202] [260]	[198]	[197] [198] [201] [202] [260]	[198]		
2007	[28] [212] [213] [214] [215] [216] [217] [219] [220] [221]	[218] [214]	[222]			[222]		
2006			[232] [233] [234]		[232]	[234]		
2005	[244]		[245]	[245]	[245]			
2004			[249]	[250]	[250]		[250]	
2003			[253] [254]		[253] [254]			
2000			[258] [259]		[259]			

in [201]. The benefits of the system with respect to learning and enjoyment were measured in [177], and the ease of use for both students and teachers in [88]. Evaluation tools used were: the Technology Acceptance Model (TAM) [261] in [88]; the System

Usability Scale (SUS) [262] in [6] and [64]; the General Interest Structure Test (AIST) [263] in [180]; interviews in [178]; observations in [179] and [200]; recording participants' interactions and collecting think aloud protocols in [5].

- *Task support.* Learners were supported in achieving their current learning goals in [170] and [177], as well as to accomplish their learning or

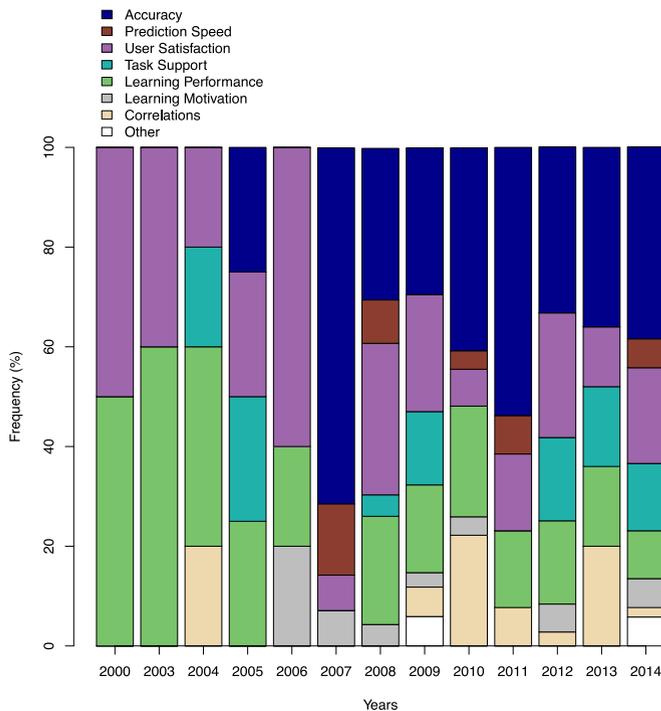


Fig. 4. Effects measured (frequency per year).

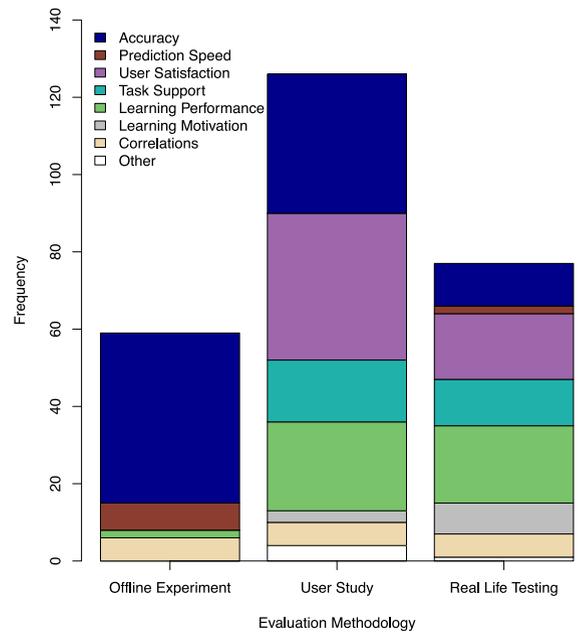


Fig. 5. Effects measured by evaluation methodologies.

authoring tasks in [5]. The effectiveness and applicability of the recommendations in supporting learning tasks were also measured in [82]. The impact of recommendations on learners were analysed by observing the learner's interactions via system logs in [6].

- *Learning performance.* The perceived effectiveness of learning using the recommender system was measured in [232]. The learner's achievements and scores in tests were measured in [6], [86] and [88]. It was also measured if students using a recommender system achieve better results than students receiving random or no recommendations in [156]. The learner's reading frequency per post, the learner's replying and posting frequency were measured in [116], as well as the frequency with which a learning activity was executed in [170]. Tools used were: pre-knowledge and post-tests in [6], [156] and [232], assignment grades in [86], and usage log analysis in [6], [86] and [170]. Learning styles were measured in [201] and [232], and using the Felder-Soloman Index of Learning Styles (ILS) questionnaire [264] in [141]. Knowledge levels were measured using self- and peer-assessments and applying Knowledge Indicating Events (KIE) in [92].
- *Learning motivation.* was measured using a learning motivation questionnaire, e.g. Motivated Strategies for Learning Questionnaire (MSLQ) [18] in [155] and the learner's engagement in terms of their connection behaviour in [6].
- *Correlations.* were measured for example between the rank position of a learning goal and the frequency with which a learning activity was executed in [170]. Metrics used were for example: Pearson correlation in [85] and Kendall's Tau correlation in [146].
- *Other.* Very few other effects were measured. The novelty and diversity of learning resources recommended were measured with a crowdsourcing experiment in [66], the variety of learning paths in [184], creativity and competence preferences in [180], and emotions in [6] and [67].

## 6 DISCUSSION AND CONCLUSION

From the results of the survey, the evaluation of TEL recommender systems viewed as early as 2000 up till 2014, has undergone various changes. The number of publications reporting on TEL recommender systems has increased, as well as those reporting on their evaluations. The different effects measured have become more numerous and diverse. The type of evaluation methodology applied has also evolved over time to a mixture of all three types identified in this survey. These findings suggest that there is a growing awareness of the necessity for elaborate evaluations in the research community. At the same time, there is substantial potential for further improvements. Selected indicators from the survey show this. About 42 percent of the publications surveyed had no evaluation. The number of participants in user studies has remained rather low over the years. Learning related measures are insufficiently considered in most of the evaluations. On a qualitative level, it has to be mentioned

that from those publications having an evaluation, only few stated a clear evaluation focus. The evaluation goals were not always clearly defined and the scope of the evaluations were often much too wide. The form in which evaluation goals, methods and results are reported in TEL research publications needs to be improved.

Regarding evaluation methodologies, on the one hand, offline experiments that are fast and easy to conduct, are limited by the fact that TEL datasets fulfilling all necessary requirements are not always available. The dataTEL initiative extensively looked into issues regarding collecting shareable datasets for TEL and proposed some guidelines on how best to accomplish this [265]. A framework for analysing TEL datasets has been proposed, existing TEL datasets have been identified and analysed in detail [3], [23] and even applied to effectively evaluate and compare several recommender systems [21]. Additionally, a survey of linked data and social data as a source of datasets for evaluating TEL recommender systems has been investigated [24]. Remaining open challenges are privacy, quality and legal issues surrounding this type of data, as well as the issues of interoperability and integration of data across different systems with no common schema and vocabularies [24]. Recently, MOOCs (*Massive Open Online Courses*) [266] have become very popular and have been used to provide a source of historical datasets for offline evaluations, for example from the popular MOOC Coursera<sup>17</sup> which provided a dataset used to evaluate a question recommender for TEL [58]. A further limitation of offline experiments is that a high prediction accuracy does not always correlate with high user satisfaction [16], [17], [82]. Presently, the most often measured evaluation criteria are precision and accuracy [3]. The survey confirms this is also true for the evaluation of TEL recommender systems. There are however many other important user-centric properties that should be considered such as novelty, diversity, privacy and serendipity [15], [16] as explained in Section 2. However in the results of the survey, these effects were rarely reported as being explicitly evaluated. On the other hand, user studies that could measure these user-centric properties face the challenges of high execution costs and having limited access to sufficient participants. From the survey, on average, about 50 participants take part in a single user study and user studies are hardly repeated in order to confirm results [15]. Therefore alternative approaches to evaluate recommender systems such as crowdsourcing should be taken into consideration where sufficient participants are recruited online via crowdsourcing platforms [57], [66], [90], [267].

There is some evidence that there are still many challenges facing the evaluation of recommender systems for TEL [5]. Evaluating recommender systems is a complicated process and complex research questions need to be broken down into smaller and more measurable sub-questions. Approaches to do this exist such as using the *layered evaluation approach* [4], [268], [269] which decomposes a recommender system into its integral components and each of these components is evaluated separately applying appropriate evaluation methods and metrics. It thereby provides developers and researchers with more

17. <http://www.coursera.org>, retrieved 20.05.2015

detailed evaluation results which could be used to improve the recommender system [4]. The layered evaluation approach has been applied to evaluate recommender systems for TEL [4], [158]. Improvements can however be made in the decomposition of the recommender system into its individual components and by defining practical guidelines to map which recommender system component can be best evaluated with which method and which metric. An overall result of the evaluations of the different components needs also to be made in order to be able to analyse the individual results and make concrete trade-off decisions to benefit the system as a whole [78]. The evaluation of recommender systems for TEL should no longer be seen as a *summative* or final assessment of the system, but should rather be integrated already in the requirements, design and implementation stages of their development aiming for a more *formative* type of evaluation [270]. The user should be placed in the centre of the development process as proposed in [6], where user centred design methods are applied along the entire e-learning life cycle including both the design and evaluation of recommender systems for TEL.

There is also the need to standardise the evaluation process in order to be able to compare the evaluation results between TEL recommender systems. An evaluation framework for comparing TEL tools and systems in data competitions has been developed [271]. Although the framework does not specifically focus on recommender systems, it gives a good insight into the specific issues and evaluation criteria to be considered when evaluating TEL systems in general. These could be applied to the domain of TEL recommender systems. Finally, the evaluation of TEL recommender systems needs to be a joint effort between computer scientists and experts from other domains like pedagogics and psychology [6]. The evaluation of TEL recommender systems needs to focus more on the impact of the recommendations during learning. As yet, little is known about the way learners perceive and react to recommendations [2]. Therefore, more real life testing of TEL recommender systems over a longer period of time is needed, where the effect of the recommender system on learners, their acceptance and usage of the recommendations can be measured [3]. As shown in [6], MOOCs provide an opportunity for conducting real life testing of TEL recommender systems with a large number of learners and over a long period of time.

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