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Review

A systematic review of scholar context-aware recommender systems

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ABSTRACT

Incorporating contextual information in recommender systems is an effective approach to create more accurate and relevant recommendations. This review has been conducted to identify the contextual information and methods used for making recommendations in digital libraries as well as the way researchers understood and used relevant contextual information from the years 2001 to 2013 based on the Kitchenham systematic review methodology. The results indicated that contextual information incorporated into recommendations can be categorised into three contexts, namely users' context, document's context, and environment context. In addition, the classical approaches such as collaborative filtering were employed more than the other approaches. Researchers have understood and exploited relevant contextual information through four ways, including citation of past studies, citation of past definitions, self-definitions, and field-query researches; however, citation of the past studies has been the most popular method. This review highlights the need for more investigations on the concept of context from user viewpoint in scholarly domains. It also discusses the way a context-aware recommender system can be effectively designed and implemented in digital libraries. Additionally, a few recommendations for future investigations on scholarly recommender systems are proposed.

1. Introduction

Recommender Systems (RSs) have been an area of substantial research interest since the mid-1990s (Felfernig & Burke, 2008). In the last decade, RSs had been investigated and implemented in various application domains, including knowledge management, e-commerce, e-learning and e-health (Verbert, Lindstaedt, & Gillet, 2010).

The dramatic data increase in *Digital Libraries* (*DLs*) has necessitated the use of RSs as an appropriate tool for facilitating and accelerating the process of information seeking (Porcel & Herrera-Viedma, 2010). Scientists prefer to have most of their required information at their fingertips. They usually input keywords to retrieve the desired scientific information in DLs, but the results may not always be what they would expect. Hence, the retrieval of relevant information has been a time-consuming task for most of them. Consequently, providing proper information is a significant factor for an effective DL in a scientific environment. Libraries try to apply intelligent personalised systems such as RSs (Mönnich & Spiering, 2008) to support users by offering relevant resources based on their interests and preferences (Sikka, Dhankhar, & Rana, 2012). RSs can manage information overload by filtering and personalising data according to users' needs (Adomavicius, Sankaranarayanan, Sen, & Tuzhilin, 2005; Pommeranz, Broekens, Wiggers, Brinkman, & Jonker, 2012); thus, RSs normally collect data about users' activities and build user models to filter the preferences expressed either explicitly or implicitly (Baltrunas, Ludwig, Peer, & Ricci, 2012).

In recent years, RSs use the information describing users' situations such as location, time, and task in order to generate more relevant and personalised recommendations (Adomavicius & Tuzhilin, 2011; Asabere, 2013). For example, the resources recommended to an undergraduate student searching for "Fuzzy method" for his class assignment may be different from those recommended to a graduate student writing a research paper on the same topic. This is due to the different requirements of the tasks they are working on and the different levels of formal education, which are considered as contextual information.

Using contextual information has been considered as a main source of accuracy of recommendations (Adomavicius & Tuzhilin, 2011; Baltrunas L. & In: Proceedings of the, 2008). Researchers emphasise applying contextual approaches in order to recommend items to users based on certain circumstances (Baltrunas & Ricci, 2009; Kaminskas & Ricci, 2011). However, the variety of application scenarios and user requirements cause difficulties in presenting an unanimous definition of contextual information for

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all *Context-Aware Recommender Systems* (*CARS*) (Yujie & Licai, 2010). Moreover, to predict accurate recommendations for users of a specific domain such as DLs, it is essential to understand and exploit the relevant contexts of users, which lead to creating intelligent recommendations. Therefore, the aim of this study is to carry out a literature review on RSs for the academic DLs in order to:

(a) Identify the contextual information that has been adopted for making recommendations in the academic DLs.
(b) Identify the approaches that have been used to adopt contextual information for making recommendations in the academic DLs.
(c) Explore how the relevance of contextual information to recommendations for an academic domain has been understood by researchers before applying it.

We conducted this review based on the guidelines by Kitchenham and Charters (2007) for performing systematic literature reviews in software engineering. We explain more about the methodology of our review in Section 4. The rest of the paper is organised as follows. We discuss a few definitions of context from various points of views and provide recommendation approaches in Section 2. The related works are presented in Section 3. The methodology of this study is presented in Section 4. We report and discuss the results from performing the review in Section 5. The results are structured according to the research questions.

2. Background

2.1. What is context?

Many definitions of context have been proposed in various disciplines, including computer science (primarily in artificial intelligence and ubiquitous computing,), information retrieval, cognitive science, linguistics, philosophy, social science, psychology, and organisational sciences (Adomavicius & Tuzhilin, 2011); it is beyond the scope of this research to review all of them. However, from a general point of view, the Oxford Advanced Learner's Dictionary mentions that context is "a situation in which something happens and that helps you to understand it" (Crowther, 1995). Likewise, according to the Webster's dictionary (Webster, 2006), "Context is a situation in which something happens: the group of conditions that exist where and when something happens".

In the late twentieth century, the epistemological contextualisation was developed by philosophers. This theory indicates that the standards of knowledge and justification change with the context. Particularly, understanding of context is necessary for better comprehension of a situation since when the context shifts, the knowledge about the situation will shift as well (Craig, 1998).

The term context appeared in computer science in the late 1980s (Hong, Suh, & Kim, 2009), and the idea of context awareness in computing was introduced by Schilit in 1994 (Brown, Bovey, & Chen, 1997) in order to increase the richness of communication and provide more useful computational services (Dey, 2001). Since then, many studies in the field of computer science tried to define the term "context". Some studies present parametric definitions that stipulate context as a set of parameters such as time, temperature, lightness, and speed, while others define context generally and try to explain context and its territories. For example, Schilit and Theimer (1994) defined context as location, identity, nearby people, and objects. In a similar definition by Brown et al. (1997), context consists of location, identity, nearby people and objects and season. Meanwhile, (Pascoe, 1998) explained that context corresponds to the following questions:

1. Where are you?
2. Who are you with?
3. What resources are nearby?

One of the most cited definitions from a computer science viewpoint was offered by Abowd et al. (1999) as shown by Fig. 1. They expressed that context is any information that can be used to characterise the situation of an entity. They categorised context into four dimensions: location, identity, time, and activity. In this definition, there are two context levels: primary contexts, which are the four mentioned dimensions and secondary contexts gained from primary contexts. As an illustration, many pieces of related information such as phone numbers, addresses, email addresses, birth date, etc., can be acquired from the location of an entity. Such information acquired from primary contexts is numerated as secondary contexts.

In another computer science point of view, (Lieberman & Selker, 2000) interpreted context as "everything" that "affects the computation except the explicit input and output", including the state of user, physical environment, computational environment, and history of user–computer environmental interaction. Dourish (2004) expressed the context as "the features of the environment within which the activity takes place", and indicated that it is separate from the activity itself. He assumed that the context was defined with a predefined set of observable attributes, the structure of which does not change significantly over time. As shown in Fig. 2, (Haseloff, 2005) presented a model of contextual factors based on Object Oriented (OO) concepts and Unified Modelling Language (UML), including surroundings, state, location and reachability.

Bazire and Brézillon (2005) identified the main components of context by analysing 150 definitions coming mainly from the web in different domains. However, they concluded that it is difficult to reach a consensus on what exactly context is. Thus, trying to reach a consensual definition for context is an ineffectual effort since the concept of "context" evokes different impressions in each reader and context may include almost everything (Kocaballı & Koçyiğit, 2007). Furthermore, it is difficult to present a definition that encompass all the aspects it refers to Tamine-Lechani, Boughanem, and Daoud (2010).

Adomavicius and Tuzhilin (2011) discussed the concept of context in recommender systems and explained how it is defined in different fields related to RSs such as data mining, e-commerce personalisation, databases, information retrieval, ubiquitous and mobile context-aware systems, marketing, and management. They confirmed that context is a multifaceted concept and there is no commonly accepted definition of context in different fields. The definition of context in RSs was investigated by Verbert et al. (2010) while contextual information is considered as any additional information that has a direct impact on the relevance of recommendations. The above definitions demonstrate that the concept of context in RSs is a crude concept. Besides, the concept of context in various domains like academic DLs differs from other domains. In other words, the nature of academic domain influences recommendations. Creating recommendations for users in an academic domain to cater to their needs and tasks needs more analysis of contextual information affecting decision-making in this

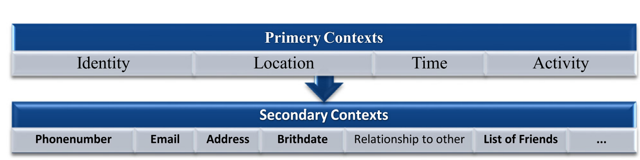

Fig. 1. Context levels offered by Dey and Abowd.

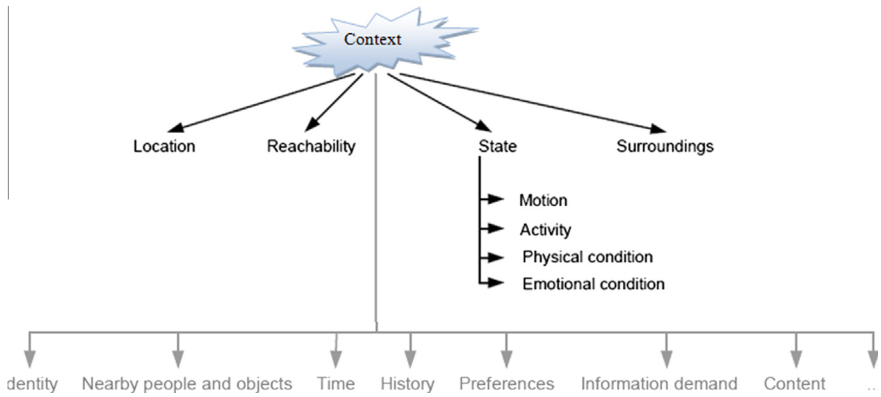

Fig. 2. Constituent elements of context.

domain. Hence, the main contribution of this paper is to review the past studies done on RSs for academic DLs in order to explore the contextual information affecting recommendations.

2.2. Recommendation approaches

RSs provide recommendations via two approaches: (1) Classical approaches and (2) Contextual approaches. In the following section, we explain the two approaches briefly.

2.2.1. Classical or two dimensional (2D) approaches

The most common systems use classical approaches, which fall into three main classes: *Content-Based* (*CB*), *Collaborative Filtering* (*CF*), and *Knowledge-Based* (*KB*) (Adomavicius & Tuzhilin, 2005). There is another class that is a combination of two or all of these three approaches, called *Hybrid* (Adomavicius et al., 2005). In this section, we first discuss the classical approaches. Classical RSs use a set of ratings that is either explicitly created by users or is implicitly deduced by a system (Adomavicius & Tuzhilin, 2011) so that two types of entities, namely users and items (two-dimensions), are used to estimate the rating function *R* (Liu, 2013):

$$R : User \times Item \rightarrow Rating$$

For each user u, the item i' that maximises the user's utility is defined as (Adomavicius et al., 2005):

$$\forall u \in U,\ i'_u = \arg\max R(u, i),\ i \in I$$

CF approaches recommend items to a target user based on given ratings by other users' behaviour similarities and users' functional patterns in the community (Lika, Kolomvatsos, & Hadjiefthymiades, 2013). CF is the most commonly used approach for creating recommendations based on previous users' search history. In particular, users looking for information should be able to utilise what other users have already found and evaluated (Zhang, Wang, & Li, 2008). On the other hand, the objectives of CB approaches focus on finding correlations between content of items as opposed to correlation between users as is the case in collaborative filtering approaches (Liu, 2013). The root of the CB approach can be traced back to Information Retrieval (IR) (Balabanović & Shoham, 1997). A comparison between CF and CB is presented in Table 1 (Burke, 2002; Vivacqua, Oliveira, & de Souza, 2009).

KB approaches employ knowledge about users and products (items) providing a system to deduce applicable links between user requirements and items that might be required to fulfil them (Resnick & Varian, 1997). KB-based systems use intelligent methods such as Neural networks, Fuzzy logic, Genetic algorithms, decision trees, and case base reasoning (Will, Srinivasan, Im, & Wu, 2009).

Since the aforementioned approaches have shortcomings (Burke, 2002; Vivacqua et al., 2009), the Hybrid approach is utilised to reduce the limitations and improve the system efficiency. For example, CF approaches can be useful if a superabundant number of users' behaviours have been identified as well as an adequate number of rated items have been accounted for. On the other hand, CB approaches are extremely dependent on content; if the content does not include adequate information to differentiate a user's preferred items from those items the user does not like, no helpful recommendation can be made (Verbert et al., 2010).

2.3. Contextual or multi-dimensional approaches

The promise of CARS is incorporating contextual information into the classical recommendation process in order to more accurately predict users' tastes and preferences (Baltrunas & Ricci, 2009). The preferences are estimated with the rating function of items, users and context as follows:

$$R : User \times Item \times Context \rightarrow Rating$$

If we define the contextual information with a set of contextual dimensions D, while two of these dimensions are *User* and *Item*, and the rest are contextual, the rating function R is:

$$R = D_1 \times D_2 \times D_3 \times \cdots \times D_n \rightarrow Ratings$$

Table 1
Comparison between content-based filtering and collaborative filtering systems.

	Content-based filtering (CB)	Collaborative filtering (CF)
Advantages	A user can receive proper recommendations without help from other users	A user may have chances to receive items that s/he never searched for before, but may be of his/her potential interests
	It is more feasible to tackle the problems of multiple users' interests and interest transference by monitoring the change and evolving of user profiles	Facilitate the sharing of knowledge and/or experiences among users having similar interest
Limitations	Some types of items (e.g. multimedia) are not easy to analyse	It is hard to provide recommendations for users that have unusual preferences
	A user can just receive items that are similar to his/her past experiences	It is difficult to cluster and classify users with changing and/or evolving preferences

The utility function is defined by selecting certain "what" dimensions $D_{i1}, \ldots, D_{ik}$ ($k < n$) and certain "for whom" dimensions $D_{j1}, \ldots, D_{jl}$ ($l < n$) that do not overlap, i.e. $\{D_{i1}, \ldots, D_{ik}\} \cap \{D_{j1}, \ldots, D_{jl}\} = \emptyset$, and recommending for each tuple $(d_{j1}, \ldots, d_{jl}) \in D_{j1} \times \cdots \times D_{jl}$ the tuple $(d_{i1}, \ldots, d_{ik}) \in D_{i1} \times \cdots \times D_{ik}$ that maximises rating $R(d_1, \ldots, d_n)$ (Adomavicius & Tuzhilin, 2011). In particular:

$$\forall (d_{j1}, \ldots, d_{jl}) \in D_{j1} \times \cdots \times D_{jl},\ (d_{i1}, \ldots, d_{ik})$$

$$= \arg\max R(d'_1, \ldots, d'_n)$$

$$(d'_{i1}, \ldots, d'_{ik}) \in D_{i1} \times \cdots \times D_{ik}$$

$$(d'_{j1}, \ldots, d'_{jl}) = (d_{j1}, \ldots, d_{jl})$$

For example, in book (i.e. item) recommendations to students (i.e. user), we have:

- Item is defined as Book (bookISBN, author, subject, publisher, year).
- User is defined as Student (studentID, name, age, degree, area).

The contextual information associated with RS in DL has the following definitions:

- Context is defined as *Location*, where the student is looking for book; *L = {university, home}*.
- Context is defined as *Time*, when the student is looking for a book; *T = {first semester, second semester}*.

Hence, in book recommendations the function will become *R = Student* × *Book* × *Location* × *Time* (Adomavicius & Tuzhilin, 2011). Contextual approaches are classified into three approaches as shown in Fig. 3: pre-filtering, post-filtering, and contextual modelling (Adomavicius & Tuzhilin, 2011).

Particularly, in contextual pre-filtering (Fig. 3a), the contextual information is used before all the ranked recommendations are computed. The reduction-based approach (Adomavicius et al., 2005) is an example of pre-filtering in which, first, all ranked recommendations are computed through classical methods like CB; then they are adjusted or re-ranked for each user using contextual information (Adomavicius & Tuzhilin, 2005). Panniello, Tuzhilin, Gorgoglione, Palmisano, & Pedone, 2009 presented a post-filtering strategy (Fig. 3b) that penalises the recommendations of items with few ratings in the target context (Campos, Fernández-Tobías, Cantador, & Díez, 2013). In contextual modelling (Fig. 3c), the contextual information is employed directly as a main part of learning preference models (built using techniques such as decision tree, regression, and probabilistic model). To put it differently, contextual variables are added as dimensions in the recommendation function in addition to the user and item dimensions.

Recently, researchers have started to improve classical recommendations by modelling contextual information. In this regard, contextual information plays an important role in recommendation for two reasons (Baltrunas et al., 2012). First, it can present the status of people, places, objects and devices in the environment. Second, contextual information may improve the accuracy of CARSs in DLs. Nevertheless, identification of valid contextual information for different domains are challenges that should be considered (Yujie & Licai, 2010). Furthermore, the methods employed for making contextual recommendations have established a paradigm shift in the field of RSs (Adomavicius & Jannach, 2013).

3. Related work

Although there are numerous studies on context-aware systems, there is no systematic review on CARSs in academic DLs as well as no study to review contextual information incorporated into recommendations in academic DLs. Nonetheless, a few reviews in the field of RSs in DLs or classifications of RSs in DLs can be helpful in identifying the need for a systematic review in this area. Hence, we discuss them as below.

A literature review conducted by (Park, Kim, Choi, & Kim, 2012) examined research done from 2001 to 2010. This study focused on classification of RSs based on their application fields and recommendation methods. According to this study, the majority of the research papers were done in the field of movie applications (53 out of 210 research papers, or 25.2%). The second and third ranks of RSs are for shopping (42 out of 210 research papers or 20.0%) and book (documents) (31 out of 210 research papers, 18.0%). They mentioned that the scope of RSs researches on books and documents has increased since 2007.

In 2008, a survey of recommender services for scientific DLs was performed by Franke, Geyer-Schulz, and Neumann (2008). They listed a few RSs used in DLs but it was found that some RSs such as Amazon and CiteSeer did not have the qualities of proper scientific DLs; hence, they were excluded. Moreover, the scientific organisations such as IEEE Xplore and ACM did not present the recommending methods employed in RSs and they faced some limitations to review them. They argued that although scientific RSs have

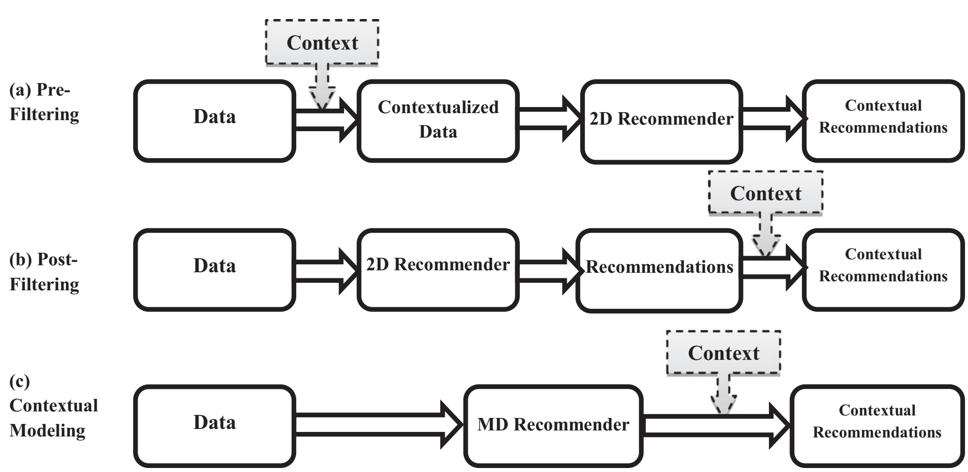

Fig. 3. The incorporation of context in the recommendation process.

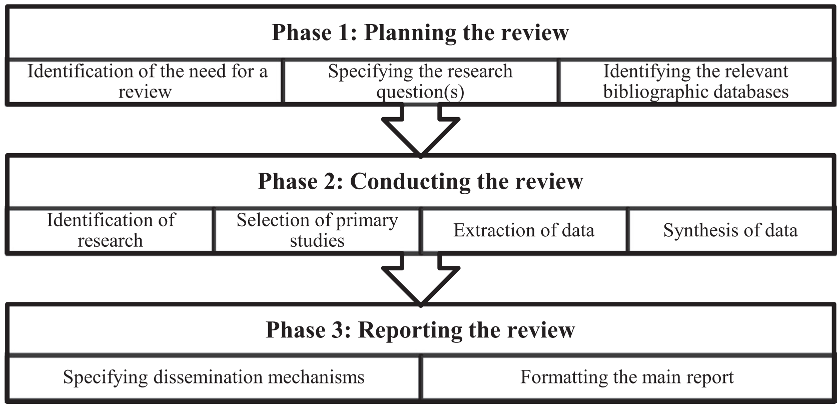

Fig. 4. Systematic literature review phases and activities.

considerable benefits for students and scientists, they are not applicable in DLs as the current interest of RSs trends towards social spaces and societies (Franke et al., 2008).

In another study, (Gottwald & Koch, 2011) conducted a survey on RSs in DLs, especially in scientific areas. The survey and the description of solutions show that a totally satisfying approach for recommending publications does not exist; hence, the scientists are not very satisfied with the retrieved information and this field needs further investigations in order to create a RS that can understand the topic of publication and recommend relevant information. The authors presented a set of semantic and non-semantic solutions with different methods and analysed them. They also provided a forecast for future development of a RS for ZIB[1] (Gottwald and Koch, 2011).

Recommendation algorithms and evaluation metrics were reviewed by Lü et al. (2012). The authors discussed recommendation approaches and basic concepts of collaborative filtering. They evaluated the available algorithms and examined their roles in recommendations. In another study, Herther (2012) presented a list of web-based RSs and gave a brief description of each RS. Most of the web-based RSs were derived from the research projects and there was not much information or published materials about the methods and the mechanics of generating recommendation.

(Beel, Genzmehr, Langer, Nürnberger, & Gipp, 2013; Beel et al., 2013 have introduced and evaluated more than 80 approaches for academic recommendations, including 170 research articles, as well as patents, presentations and blogs. They accomplished three main evaluations: user's studies, offline and online to determine which approaches are the best performing, and their respective strengths and weaknesses. They discovered that users usually do not rate papers in recommender systems. Therefore, it is not easy to evaluate the performance of recommender systems through the users' ratings. To solve this problem, implicit rating such as citing, and downloading are considered. For example, if a user writes a paper and cites articles, the citations are considered as positive rates of the cited articles. They finally concluded that it is currently not possible to determine which recommendation approaches for academic purpose are the most promising. However, there is little value in the more than 80 existing approaches if the best performing approaches are unknown.

4. Methodology

We used the systematic literature review methodology introduced by Kitchenham and Charters (2007) since it is a rigorous and well-defined method in the fields of software engineering. As the word systematic indicates, systematic literature review aims to specify questions and review relevant studies in order to identify gaps in the current research, as well as appraise their contributions to questions and gaps for drawing conclusion in a particular research question, area, or phenomenon. As shown in Fig. 4, we did this review in three phases. Each phase is explained in the following sections.

4.1. Planning the review (Phase 1)

During the planning phase, we identified the objectives of the review and conducted the following activities that specified every step in detail.

4.1.1. Identification of the need for a review

In Phase 1, we determined that there was no systematic review in the field of CARSs for DLs. The increasing number of papers on CARSs in many disciplines (such as ubiquitous and mobile computing, e-commerce, marketing, information retrieval, and many others) is ample evidence that applying contextual information had been a critical issue in the last decade (Adomavicius & Jannach, 2013). Identifying contextual information used in RSs for an academic domain is effective for future studies in this field. Hence, we identified the need to conduct a systematic review based on the results from the past studies that exploited contextual information for recommendations in DLs.

4.1.2. Specifying the research question(s)

As an important activity in Phase 1, we came up with the following three questions as the focus of this review:

1. What contextual information has been adopted for making recommendations in academic DLs?
2. What approaches have been used to adopt contextual information for making recommendations in academic DLs?
3. How has the relevance of contextual information on recommendations for an academic domain been understood by researchers before applying it?

4.1.3. Identifying the relevant bibliographic databases

In response to the aforementioned questions, we chose the bibliographic databases that cover the majority of journals and conference papers published in the field of computer science in order to find the relevant studies for the review (Activity 3, Phase 1). We identified the following bibliographic databases as relevant: ACM, Ebsco, Web of Science, Proquest, IEEE, ScienceDirect, SpringerLink, Emerald, Google Scholar, and Ingenta Journals. In

[1] Zuse Institute Berlin.

addition, we performed searches in LIS databases such as SAGE Journals, LL& IS (H.W. Wilson), LISA (LISAbstracts). Setting a starting and closing date for the review is one of the guidelines of this systematic review, as mentioned in the study by Stapić, López, Cabot, de Marcos Ortega, and Strahonja (2012). As the first CARS was created by a hybrid approach of CF and CB (Herlocker & Konstan, 2001) in 2001, January 2001 was chosen as the starting date of the review, and this study covers related papers published from then until November 2013. The searches were limited to journal and conference proceedings papers that were published within the above period.

4.2. Conducting the review (Phase 2)

In previous studies, various terms have been used for CARSs such as context-aware RS, context-aware recommendations, contextual recommendation, contextual RS, and context-dependent RS (Baltrunas & Ricci, 2009). Likewise, different terms and synonyms have been used for academic DLs, including scholar DLs, university DLs, and scientific DLs (Porcel & Herrera-Viedma, 2010). In this review, we targeted those digital libraries designed for an academic domain and used by students, faculty members, researchers or scientists, like those found in a university with scientific collection (book, paper, and document). Thus, in order to retrieve the maximum number of relevant papers, we carried out searches in bibliographic databases through two steps. In the first step, the searches were specified to retrieve the papers discussing directly CARSs in academic DLs by "boolean strategy" in their title, abstract and keywords; a total of 12 papers were retrieved through this step. The search strategy is depicted in Fig. 5.

Some of the studies exploited contextual information to generate recommendations for academic DLs but did not mention the terms "contextual" or "context aware" as well as "academic" directly in their titles or abstracts. Therefore, we used a broader strategy in our search in order to find those papers focusing on RSs in DLs by reviewing the title, abstract and keywords (Fig. 5 second step). After conducting the second step, an additional 126 papers that discussed RSs for recommending books, documents, and papers from 2000 to 2013 were identified. We added all of them to our database (i.e. Fig. 4, Phase 2, Activity 1). Thus, the total number of papers retrieved through the two search steps was 138 papers.

4.2.1. Identification and selection of primary studies

We reviewed the papers through the abstract, introduction and conclusion. Among the retrieved papers, we selected papers that were written in English and that met at least one of the following criteria:

- The paper discussed RSs for academic, scholarly, scientific or university DLs.
- The paper discussed RSs for book, paper or article recommendations.
- The paper discussed RSs methods or models for academic, scholarly, scientific, university DLs or paper, article or document recommendations.
- The experiment data set for recommendations was one of the above domains even though the paper did not mention explicitly any of the above terms in the title and abstract.
- The recommendations had been created specifically for students, faculty members, researchers or scientists even though the paper did not mention explicitly any of the above terms in the title and abstract.

We also considered a few additional exclusion criteria as follows:

- The relevant resources that were described in thesis, technical reports and other documents had no peer review assessment.
- The papers that discussed RSs in other parts of digital library services, such as collection acquisition, materials selection, organisation and cataloguing, and dissemination of information. For example, (Yang & Hung, 2012) presented a model of recommendations for book-acquisition.
- The RSs that have been implemented in universities but without any published paper discussing the recommendations process. For example, (Hahn, 2011) reviewed a few web-based university RSs, but there are no published materials about the process of making recommendation.
- The RSs that were applied in some online DLs such as ACM digital library, IEEE, Ebsco, and ProQuest. As mentioned before, there is not enough information or published papers for some online DLs (Franke et al., 2008).

4.2.2. Data extraction and synthesis

Considering the aforementioned criteria, 80 papers were selected for final review in order to provide answers to the identified questions. As discussed in Section 3, we cannot enumerate specifically which piece of information is considered as contextual information, and we cannot determine a specific definition of context. Moreover, through reviewing a few papers, we noted that some studies did not use the term "context" but they considered some criteria to create recommendations that are more relevant. As an illustration, in a study by Basu, Cohen, Hirsh, and Nevill-Manning (2011), there is not any trace of the term "context" or "contextual information". Instead, they considered criteria such as reviewer description for making recommendations. Another study stated that Google Wave information was applied to create better recommendations in a university DL (Serrano-Guerrero, Herrera-Viedma, Olivas, Cerezo, & Romero, 2011). Hence, in this review, contextual information is regarded as any information that

	Term 1		Term2		Term3	Search results
First Step	contextual OR context-dependent OR context aware	AND	recommender system recommendation	AND	academic DL OR scholar DL OR scientific DL OR university DL	12 papers

	Term 1		Term 2	Search results
Second Step	recommender system OR recommendation	AND	library	126

Fig. 5. Search strategies.

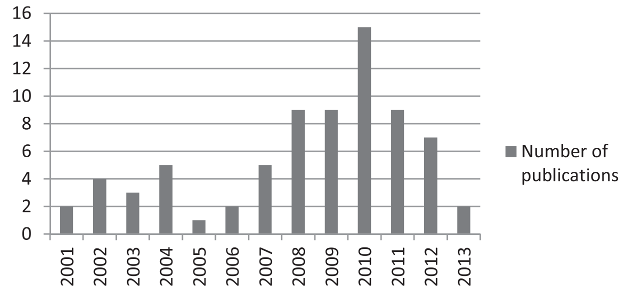

Fig. 6. Distribution of the selected papers from 2001 to 2013.

describes a situation or scenario of persons or objects leading to better recommendations for users in academic DLs.

Considering the above definition of context, 80 papers that satisfied the filtering criteria were selected. Fig. 6 shows the distribution of the selected papers from 2001 to 2013. Next, we reviewed the complete text of the 74 papers and classified them. The classification process is explained in Section 5.

4.2.3. Validity control

From the 138 primary retrieved papers, 28 (20%) were randomly selected and reviewed by another author of this study based on their abstract, introduction and conclusion in order to certify the accuracy of the 80 selected papers for data extraction and analysis. Among the 28 papers randomly chosen from the 80 papers, 22 papers met the criteria.

In order to control the maximum number of relevant studies, we established another control. We reviewed the list of references of the 80 selected papers and crosschecked the titles of references with our database. The additional control resulted in a discovery of one new relevant paper that met the aforementioned criteria. The paper was included in our database for data extraction; hence, the number of relevant papers increased to 81. The additional control confirmed that the maximum number of relevant papers in the scope of this paper had been considered.

In order to ensure the validity of categorisation of results, another control was used by randomly selecting 16 papers (20%) of the 81 selected papers. The second author classified the selected papers without any knowledge of the first author's rankings. In this case, there was one deviation in the classifications of contextual information. After analysing the deviation, one classification of contextual information was added to the results.

5. Results

In this section, we report the results (Phase 3: reporting the review) of this systematic review and discuss them in order to respond to the three questions posed in Section 1.

5.1. What contextual information has been adopted for RSs in academic DLs?

The results taken from our review showed that, contextual information exploited for RSs in academic DLs are categorised into three main groups, including user (Table 2), document (Table 3), and environment contextual information (Table 4). These categories are shown in Tables 2–4 respectively.

5.1.1. Users' contextual information

The users' contextual information implies the information explaining users' current situation. We sorted and categorised users' contextual information based on the analysis of the past studies.

5.1.1.1. User's profile. The users' profile information, including personal or demographic information, general interests and research areas is used to make recommendations. The fixed information such as identity, name, age and gender is considered as the long-term profile information. Meanwhile, information like research interests, which change consistently, is considered as the short-term information. Recommendation methods will be considered as both long-term and short-term information. The user's privacy is very critical in libraries. The process of making recommendations should not intrude the users' privacy (Ackerman & Mainwaring, 2005). In some studies, RSs make recommendations based on the desired privacy level that users have predetermined in their user profile (Bollen & Van de Sompel, 2006) (Geyer-Schulz, Neumann, & Thede, 2003a). For example, the users do like to receive recommendations taken from the circulations logs so the system must follow and protect the privacy for making the recommendations.

Additional user profile information include degree (undergraduate, graduate) (Tsai & Chen, 2008; Zhu & Wang, 2007), relation between the majors and reading materials (e.g. computer science students read the electronic books), primary article publications (Amini, Ibrahim, Othman, & Rastegari, 2011; Sugiyama & Kan, 2010), project descriptions and memberships (Krafft, Birkland, & Cramer, 2008; Martínez, Vosou, Villarreal, & De Giusti, 2010).

5.1.1.2. User types. Based on the papers reviewed in this study, the users using academic DLs are categorised into three groups: students, faculty members, and researchers. (Torres, McNee, Abel, Konstan, & Riedl, 2004) investigated recommendation satisfaction according to two types of researcher levels, namely students (master's and PhD students) and professionals (researchers and professors). However, the recommendation system modelled each researcher's interest using only one paper that the researcher must manually choose. A few studies clearly defined the users. For example, Luo, Le, & Chen, 2009 differentiated between researchers and classified researchers into two groups: junior researchers are those who have only published a single paper that has yet to attract any citations (i.e. no citation papers); and senior researchers are those who have published multiple papers where their past publications may have attracted citations. The difference is that the two types of researchers' publication lists display different properties.

5.1.1.3. Purpose/target. Users search in academic DLs for various purposes such as to maintain awareness, explore research area and find relevant sources. To make better recommendations, RSs must take information-seeking purposes into consideration (Kuo & Zhang, 2012). For example, it may be useful and satisfactory to send the last updated papers in a specific domain if the user is continually searching to obtain more information about a certain research area.

5.1.1.4. Activity/task. Different scenarios of the users' activities or tasks have been presented to support the scholarly communication process in RSs. Matching the users to their specific tasks leads to increased user satisfaction, efficiency, and usefulness of the recommender system (McNee, Kapoor, & Konstan, 2006). Rodriguez, Allen, Shinavier, and Ebersole (2009) extrapolated four kinds of activities from the investigations of the scholars' information seeking behaviours. They mentioned that the scholars' searching of the academic DLs are usually looking for:

- An article related to another article of interest.
- A potential collaborator for a funding opportunity.
- An optimal venue to submit their article.
- Referees to review an article in the role of an editor.

Table 2
Users' contextual information and its facets.

Users			
	Contextual information	Condition	References
1	Profile (Long term/short term profile)	Personal or demographic information (name, family, ID number, account, email, password, department, college, gender, age, identity national document, address, phone number, mobile phone, fax, profession, occupation, affiliation), General interests (Explicit/implicit interests, past/current interests), Research areas (Long term/sort term), Preferences (Short term/long term), Personal privacy, Current user session, Degree (Undergraduate (bachelor), graduate (PhD, Master))/Discipline/major, Relation between the majors, Primary article publications, Project descriptions, Memberships	Zhang et al. (2008), Franke et al. (2008), Webster et al. (2004), Basu et al. (2011), Geisler, McArthur, and Giersch (2001), Trujillo, Millan, and Ortiz (2007), Zhu and Wang (2007), Yang, Zhang, and Feng (2007), Herrera-Viedma, Porcel, López-Herrera, and Alonso (2008), Tsai and Chen (2008), Cheng Li et al. (2008), Rodriguez et al. (2009), Yang, Zeng, and Huang (2009), Mikawa, Izumi, and Tanaka (2011), Gantner, Rendle, Freudenthaler, and Schmidt-Thieme (2011), Dehghani et al. (2011), Nakagawa and Ito (2002), Middleton, De Roure, and Shadbolt (2002), Hwang et al. (2003), Torres et al. (2004), Middleton, Shadbolt, and De Roure (2004), Chandrasekaran, Gauch, Lakkaraju, and Luong (2008), Sugiyama and Kan (2010), Porcel, del Castillo, Cobo, RuÌz-RodrÌguez, & Herrera-Viedma (2010), Wang, Wei, Chao, and Chen (2004), Amini et al. (2011), Pennock, Horvitz, Lawrence, and Giles (2000), Konstan et al. (2005), McNee et al. (2006), Lopes, Souto, Wives, and de Oliveira (2008), Sun, Ni, and Men (2009), Luo et al., 2009; Gipp, Beel, and Hentschel (2009), Liao, Hsu, Cheng, and Chen (2010), Martínez et al. (2010), Kuo and Zhang (2012), Wu,, Yuan, Yu, and Pan (2012), Tsuji et al. (2012), Herlocker et al. (2012), Yang and Lin (2013), Carlos Porcel, López-Herrera, & Herrera-Viedma (2009), Kang and Choi (2011), Bollen and Van de Sompel (2006), Geyer-Schulz et al. (2003a), Krafft et al. (2008), De Giusti et al. (2010), Pagonis and Clark (2010)
2	Types	Student, faculty member, researcher (junior researchers: only one published paper; senior researchers: multiple publications)	Torres et al. (2004), Sugiyama and Kan (2010), Luo et al. (2009)
3	Purpose/target	Maintain awareness, explore research area, find relevant sources	Herrera-Viedma et al. (2008), Cheng Li et al. (2008), Torres et al. (2004), Luo et al. (2009), Yang and Lin (2013), Popa, Negru, Pop, and Muscalagiu (2008), Morales-del-Castillo, Peis, and Herrera-Viedma (2009), Hwang, Wei, and Liao (2010)
4	Activity/task	Scholar is in search of an article related to another article of interest, scholar is in search of a potential collaborator for a funding opportunity, scholar is in search of an optimal venue to which to submit their article, scholar, in the role of an editor, is in search of referees to review an article, paper writing (draft paper, proposal, submitted paper)/assignment	Will et al. (2009), Rodriguez et al. (2009), Dehghani et al. (2011), Nika et al. (2011), Konstan et al. (2005), McNee et al. (2006), Luo et al. (2009), Jung et al. (2004), Patton et al. (2012)
5	Pre-knowledge/ skill	In searching: Skilled (aware of search and access to digital resources); Non-skilled (not aware of search and access (The first-time user); In area: novice, experienced, experienced in a related field, experienced in a non-related field	Amini et al. (2011), Konstan et al. (2005), McNee et al. (2006), Luo et al., (2009), Wakeling (2012), Whitney and Schiff (2006), McNee et al. (2002)
6	Social networking & homepage information	Collaboration with other users, work team, coauthor relationships & connections between scholars, colleagues' work, Google Wave, Blog information/posts	Porcel, Herrera-Viedma, Enrique (2010), Hahn (2011), Serrano-Guerrero et al. (2011), Herrera-Viedma et al. (2008), Konstan et al. (2005), Porcel et al. (2010), Kuo and Zhang (2012), Wu et al. (2012),Yang and Lin (2013), Morales-del-Castillo et al. (2009), Hwang et al. (2010), Renda and Straccia (2002), Pham, Cao, Klamma, and Jarke (2011), Krafft et al. (2008), Yuan, Yu, and Zhang (2011), De Giusti et al. (2010)
7	Logs	We browsing logs (available institutions, Yahoo, Google), Search logs, Circulations logs	Geisler et al. (2001), Zhu and Wang (2007), Yang et al. (2009), Dehghani et al. (2011), Hwang et al. (2003), Tsuji et al. (2012), Middleton et al. (2004), Bollen and Van de Sompel (2006), Jung et al. (2004), Whitney and Schiff (2006), Renda and Straccia (2002), André Vellino (2010), Wang and Shao (2004), Geyer-Schulz et al. (2003b), Yang (2010), Liao, Kao, Liao, Chen, and Huang (2009), Yoshikane and Itsumura (2013), Chen et al. (2008)
8	Information behaviour	Seeking, reading, saving, downloading, printing	Trujillo et al. (2007), Cheng Li et al. (2008), Torres et al. (2004), Rocha (2001)
9	Information need level	Immediate, not immediate	Will et al. (2009), Herlocker et al. (2012), Jung et al. (2004)

There are various activities listed above because users have different tasks. For example, a user is searching for an article because she or he needs to write an assignment or a paper. The various tasks include (Dehghani, Afshar, Jamali, & Nematbakhsh, 2011; Konstan, Kapoor, McNee, & Butler, 2005; Patton, Potok, & Worley, 2012):

- Completing an assignment
- Preparing a paper
- Preparing a proposal
- Writing a thesis

All of the above activities need appropriate algorithms to support a variety of different user-level tasks and user types.

5.1.1.5. Pre-knowledge/skill. Pre-knowledge or background knowledge has been defined as the primary specific knowledge about a topic an individual has learnt formally or informally (via experience). In the academic context, it is considered as the content knowledge, academic language and vocabulary necessary for understanding content information (Strangman & Hall, 2004). According to the reviewed studies, two types of pre-knowledge, including pre-knowledge in searching and pre-knowledge in research area, were incorporated into useful recommendations for users seeking information in academic DLs. In searching, the users are separated into two categories: skilled users who are aware of search and access to digital resources; and non-skilled users who are not aware of search and access, or are also known as the first-time users. It is clear that those users who are not

Table 3
Document contextual information and its facets.

Document		
Contextual information	Condition	References
Bibliographic information	Book (ISBN, title, author, publisher, date, classification, description, keywords, format, language, status) Paper (title, authors, abstracts, keywords, URL, introduction, main idea, conclusion, description, type of paper (journal, conference, lecture notes), journal ISSN, journal clusters, standard classification (MeSH))	Mönnich and Spiering (2008), Hahn (2011), Basu et al. (2011), Geisler et al. (2001), Herrera-Viedma et al. (2008), Tsai and Chen (2008), Rodriguez et al. (2009), Yang et al. (2009), Middleton, De Roure and Shadbolt (2002), Middleton et al. (2004), Konstan et al. (2005), Sun et al. (2009), Luo et al. (2009); Gipp et al. (2009), Martínez et al. (2010), Herlocker et al. (2012), De Giusti et al. (2010), Whitney and Schiff (2006), Geyer-Schulz et al. (2003b), Renda and Straccia (2002), Yoshikane and Itsumura (2013), Chen and Yang (2010), Kapoor et al. (2007), Yang and Yun (2010), Rao and Talwar (2011), Zarrinkalam and Kahani (2013), Steinberg et al. (2010), Vellino and Zeber (2007)
Citation between papers	documents that are cited by the document/documents that cite the document/Co-citations	Franke et al. (2008), Webster et al. (2004), McNee et al. (2006), McNee et al. (2002), Wilensky (2002), He, Pei, Kifer, Mitra, and Giles (2010), Wu et al. (2012)
Popularity	The most popular papers by month and year	Hahn (2011)

Table 4
Environment contextual information and its facets.

Environment		
Contextual information	Condition	References
Location	Geographic location, location at the library	Hahn (2011), Cheng Li et al. (2008), Gantner et al. (2011), Konstan et al. (2005), Chen and Yang (2010), Aittola, Ryhänen, and Ojala (2003), Luo, Dong, Cao, and Song (2010)
Time	Assignment due (a few hours or a few days), week, semester	Hahn (2011), Cheng Li et al. (2008), Wang et al. (2004), Wu et al. (2012), Luo et al. (2010)
Service type	Connect device, connecting mode, network bandwidth	Luo et al. (2010)

skilled in searching might face many difficulties in finding useful information; for instance, undergraduate students. Hence, the RSs should identify such users and support them by offering relevant recommendations (Amini et al., 2011).

Pre-knowledge in searching has an essential impact on the process of information seeking. On top of that, the awareness of research area is a way to generate useful recommendations. (McNee et al., 2002) distributed a subjective questionnaire to students at the University of Minnesota to survey the users' information seeking behaviours. They classified students according to their pre-knowledge in research area into four categories as follows:

- Novice users:

Users in this category are not familiar with the research area. They do not know any authors, papers or specific keywords to search for the information they need. They do not even know exactly what information they are seeking. They define their needs in a language that does not match the language used in the digital library.

- Experienced users in this field:

An experienced user is defined as someone who knows how to search in the digital library and knows about the authors, papers, and keywords to express his/her information needs. Most of the users in this category are seeking information in their area of expertise. They have specific information needs and it might be not easy to meet their exact information needs. An example of a user in this category might be a professor whose area of expertise is machine learning and is searching for papers in that specific domain.

- Experienced users in a related field:

The only difference between this category and previous category is that the users are searching for information in an area that is not their field of expertise. Although they have the knowledge to carry out a search, they do not know specific authors, papers, or keywords to match their information needs to DLs. They expect RSs to help them find the appropriate information. This category of users has unclear information needs but has high expectations and demands for relevant results. For example, an artificial neural network researcher interested in bio-informatics is looking for papers about the structure of the brain (Shahamiri & Salim, 2014).

- Experienced users in a non-related field:

Although it is difficult to draw a distinction between related and non-related fields, the experienced users in a non-related field have at least one paper published, but not in the current field.

5.1.1.6. Social networking and homepage information. The collaboration with other users, work team and co-author relationships traceable by social networking is a relatively rich source of users' networks for creating relevant recommendations. For example, the users' research network of social relationships, expertise, user similarities in research areas, published papers, and preferable journals are factors exploited by RSs (Yang & Lin, 2013). In a study by Serrano-Guerrero et al. (2011), the users' information obtained from online social networks such as Google Wave is used for providing recommendations.

Assuming a graduate student A in computer science has a sub-field of machine learning, we can draw a relationship network like the relationships shown in Fig. 7. As such, the graduate student might have relationships and similar interests with colleagues, supervisors, other professors, students and experts in the same field. Each of the mentioned group has relationships with others. For example, a supervisor of student A has other students who might be similar to student A.

5.1.1.7. Logs. The effect of information taken from the web browsing logs, search logs, circulations logs and past work referenced

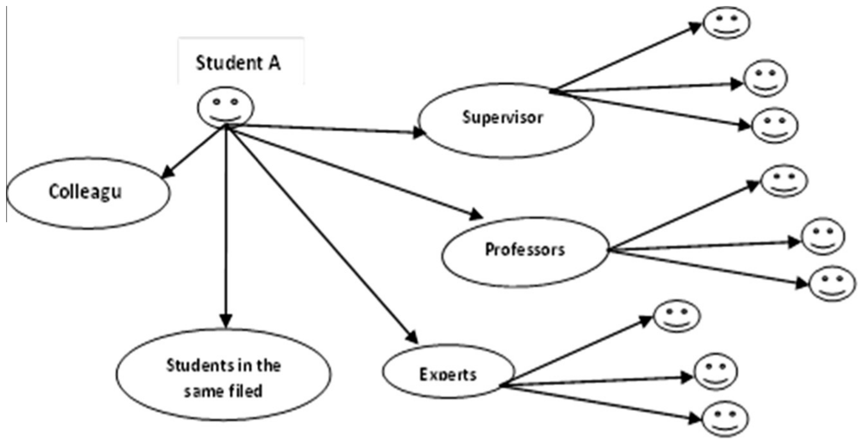

Fig. 7. Users' relationship networks.

papers on relevant recommendations was examined and presented in a few studies (Dehghani et al., 2011; Hwang, Hsiung, and Yang (2003), Jung, Harris, Webster, & Herlocker, 2004; Tsuji et al., 2012; Yoshikane & Itsumura, 2013). One of the methods explored by the Melvyl Recommender Project team for generating recommendations was using circulation data logs from the University of California, Los Angeles (UCLA) to establish linkages between items. The results of their experiments showed that recommendation sets were appropriate. They exploited the linkages between items checked out by students over time, although they could not identify each individual as a specific patron (Whitney & Schiff, 2006).

5.1.1.8. Information behaviour. The ways individuals interact with systems in order to find and utilise information are described as the information behaviour such as seeking, reading, saving, downloading and printing information (Geyer-Schulz, Neumann, & Thede, 2003b). Scholarly RSs provide models of users' information behaviours to calculate the users' preferences. For example, when a user downloads a paper (De Giusti, Villarreal, Vosou, & Martínez, 2010) or reads a paper (Cheng Li, Zhen-Hua, & Li, 2008)), it would be rated as the user' preferences.

5.1.1.9. Information need level. Sometimes, users urgently need information to perform their tasks immediately. These users need fast and direct information (Herlocker, Jung, & Webster, 2012; Will et al., 2009). For example, a student having a tight deadline and is looking for some relevant references to prepare a proposal might not like book recommendations. The results of a few studies indicated that users typically have immediate and non-immediate information needs. Considering the urgency of information plays a crucial role in ensuring users' satisfaction with the recommendations (Jung et al., 2004).

5.1.2. Document contextual information

CB approaches generally calculate the similarities between the content of documents for making recommendations. Each document has specific attributes that differ from others such as bibliographic information, citations and popularity. There are several attributes of documents (Pazzani & Billsus, 2007). For example, bibliographic information of a paper, including title, ISSN, abstracts, keywords are key factors in generation of ratings.

Like bibliographic information, co-citations are semantic similarities ratings for documents that present the frequency of two documents cited together by other documents (Franke et al., 2008). Some studies proposed approaches where they compute the similarity of citations between scientific papers to recommend appropriate papers (McNee et al., 2002; McNee et al., 2006; Webster, Jung, & Herlocker, 2004). Besides, the modelling of researcher's past works as well as papers that cite the work are effective to be used for the purpose of formulating scholarly papers recommendations. This model was implemented and tested by Sugiyama and Kan (Sugiyama & Kan, 2010). Based on the results obtained from the users' feedback, they proved that filtering these sources of information has a significant impact on accuracy of recommendation.

In designing a scholarly RS for the undergraduate library at the University of Illinois, the popularity of resources was used, which included the highest levels of loan for a specific resource during a specific time such as month or year (Hahn, 2011).

5.1.3. Environment contextual information

Environment contextual information presents a set of information to formalise the situation of users, especially when the situation of users is dynamic and changes frequently. As shown in Table 4, based on the results of our review, examples of the environment contextual information exploited for scholarly recommendations include location, time, service type and surrounding conditions. It seems that environment contextual information is mostly employed in mobile recommender systems, which are characterised by dynamic changes in the environment.

Environment contextual information can be incorporated into recommendations to ensure that users receive fast, secure and relevant resources and services in a dynamic and adaptive environment. Such context information is used to predict the user preferences for a location or specific time. SmartLibrary is a location-aware mobile library service deployed at the University of Oulu in Finland, which assists users to find library resources using a map-based guidance. If a user is not familiar with the shelf classification of resources to find the location of resources in the library, the map-based guidance, which is connected to the online catalogue of the library, retrieves the location of the resource. Based on the current user location, the system leads the users to identify the location of the resource. The SmartLibrary was evaluated by students and the results showed that students were satisfied with the recommendations. Hence, this system was implemented in the library standard customer service at the University of Oulu (Chen, Tsai, Yeh, Yu, & Bak-Sau, 2008).

5.2. What approaches have been used to adopt contextual information for making recommendations in academic DLs?

Table 5 classifies the approaches used for recommendations in order to answer the second question of this review. As can be seen, many approaches have been successfully applied to make

Table 5
Approaches used for recommendations.

Recommendation approaches	Methods	References
Collaborative Filtering (CF)	k-Nearest, k-NN Classifier, Clustering technique, Matrix Clustering, association rule mining	Webster et al. (2004), Mcnee (2006), Cheng Li et al. (2008), Gantner et al. (2011), Nakagawa and Ito (2002), Hwang et al. (2003), Sugiyama and Kan (2010), Wang et al. (2004), Pennock et al. (2000), Konstan et al. (2005), Liao et al. (2010), Kuo and Zhang (2012), Wu et al. (2012), Tsuji et al. (2012), Herlocker et al. (2012), Krafft et al. (2008), Jung et al. (2004), Wakeling (2012), McNee et al. (2002), Renda and Straccia (2002), Pham et al. (2011), Yuan et al. (2011), Geyer-Schulz et al. (2003b), Chen and Yang (2010), Aittola et al. (2003), Trujillo et al. (2007), Wang and Shao (2004)
Content- Based (CB)	Fuzzy, Knowledge networks, TF/IDF, tree algorithm, page ranked algorithm, genetic algorithm, Latent Semantic Analysis	Basu et al. (2011), Herrera-Viedma et al. (2008), Chandrasekaran et al. (2008), Porcel et al. (2010), Sun et al. (2009), Morales-del-Castillo et al. (2009), Hwang et al. (2010), Rocha (2001), Yang and Yun (2010), Rao and Talwar (2011), Steinberg et al. (2010), Pagonis and Clark (2010), Porcel, Herrera-Viedma, Enrique (2010), Franke et al. (2008), Serrano-Guerrero et al. (2011), Yang et al. (2007), Porcel et al. (2009)
Knowledge- based (KB)	Data-mining, case base reasoning method Adaptive Resonance Theory (ART)	Will et al. (2009), Tsai and Chen (2008), Rodriguez et al. (2009)
Hybrid	Semantic web, ontology, PL-CR algorithm	Andre Vellino & Zeber et al. (2007), Zhang et al. (2008), Rodriguez et al. (2009), Geisler et al. (2001), Middleton et al. (2002), Torres et al. (2004), Middleton et al. (2004), McNee et al. (2006), Popa et al. (2008), Whitney and Schiff (2006), Geyer-Schulz et al. (2003b), Kapoor et al. (2007), Luo et al. (2010), Yoshikane and Itsumura (2013), Yang (2010), Geyer-Schulz et al. (2003a)
Other methods	Cluster analysis, data mining, behaviour-based, Association rule mining algorithm, Repeat-buying Theory, Resource Description Framework (RDF), neural network, Non-parametric probabilistic model, Usage-based & Citation-based, Silhouette-based Gait Classification, ACL Anthology Network	Mönnich and Spiering (2008), Hahn (2011), Zhu and Wang (2007), Rodriguez et al. (2009), Yang et al. (2009), Mikawa et al. (2011), Middleton et al. (2002), Amini et al. (2011), Lopes et al. (2008), Luo et al. (2009), Liao et al. (2010), Martínez et al. (2010), Yang and Lin (2013), Kang and Choi (2011), Bollen and Van de Sompel (2006), De Giusti et al. (2010), Patton et al. (2012), Vellino (2010), Liao et al. (2009), Zarrinkalam and Kahani (2013), Wilensky (2002), He et al. (2010), Dehghani et al. (2011)

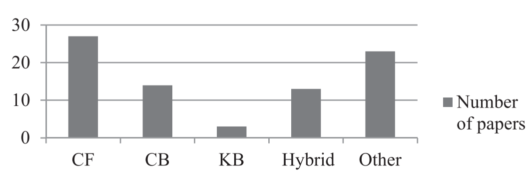

Fig. 8. Distribution of recommendation methods.

recommendations. Fig. 8 depicts the distribution of recommendation methods; the majority of approaches are typically classical approaches of CF.

Machine learning and data mining technologies were mainly applied in classical recommender systems to draw inferences of user's preferences to deal with explicit ratings or implicit user behaviours and demographic information. There are various machine-learning methods to recommend articles based on the citations of other users, which are considered as CB approaches. As an illustration, text analysis methods have been used to compare the full or partial content of a set of interesting articles to a set of potentially interesting articles using methods such as Term Frequency Inverse Document Frequency (TF-IDF), Latent Semantic Analysis (LSA), and Topic Modelling (TM) (Patton et al., 2012). Hierarchical classification, contextual graph, conceptual map, ontology, statistical methods, and Bayesian network are contextual modelling methods used in order to present the users' context. Among them, hierarchical classification and ontology are the two most frequently used methods (Liu, 2013).

However, the quality of resources has not been emphasised in most of the existing studies. Although some of the methods applied have managed to reduce information overload in DLs, they still act as an information retrieval system by applying retrieval techniques (Porcel & Herrera-Viedma, 2010; Porcel, Moreno, & Herrera-Viedma, 2009) such as clustering and text mining. This is in view of the fact that both the relevant resources that meet user needs and quality of recommendations are the key aspects of recommender systems (Tejeda-Lorente, Porcel, Peis, Sanz, & Herrera-Viedma, 2013) which distinguish them from retrieval systems. Users expect recommender systems to disseminate relevant and novel recommendations based on their current context while the results of retrieval systems are evaluated and compared with user query (Burke, 2007; Deshpande & Karypis, 2004).

A few studies impugned the effectiveness of applying users' context to recommendation. They reasoned that although the performance of recommender systems will be improved by using contextual information, incorporating contextual information into recommendations leads to greater data volume and a considerably more complex computation; this makes it even harder to estimate the important contextual factors that are relevant to user interests (Yujie & Licai, 2010). Hence, contextual approaches have been confronted with new research paradigms where the amount of library data is tremendously increasing and there are not many publications that have evaluated contextual methods and compared them with classic approaches.

Recently, most of the DLs use semantic technologies such as linked data to represent the library data (Bojārs, Lopes, & Schneider, 2013). This development has created a new research direction in recommending methods by semantic interlinking user information and recommendations in order to augment and improve the recommendations process (Dietze, Drachsler, & Giordano, 2014). The linked data approaches investigate novel strategies to find the similarities and relations between items in a database identified by cataloguing, content analysis, keyword identification and tagging. Recommendations are then made based on semantic relations between the content of the items and the preferences that a user has expressed in the past (Ostuni, Noia, Sciascio, & Mirizzi, 2013; Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994).

The results of a survey conducted by Bobadilla, Ortega, Hernando, and Gutiérrez (2013) to review the most cited papers in the field of RSs showed that the third generation of RSs has emerged, in which linked data or web of data for making recommendations is considered. Researches on the third generation of RSs trend towards contextual recommendations through the hybrid algorithms. Using linked data for building recommendation is in its infancy; hence, this area should be addressed and investigated further in future studies (Ostuni et al., 2013).

Table 6
The way of understanding the relevance of contextual information to recommendations.

The way of understanding of the relevance of contextual information on recommendations	References
The researchers have cited past studies used this contextual information	Porcel, Herrera-Viedma, Enrique (2010), Mönnich and Spiering (2008), Zhang et al. (2008), Will et al. (2009), Franke et al. (2008), Hahn (2011), Geisler et al. (2001), Zhu and Wang (2007), Yang et al. (2009), Mikawa et al. (2011), Gantner et al. (2011), Torres et al. (2004), Chandrasekaran et al. (2008), Porcel et al. (2010), Sugiyama and Kan (2010), Wang et al. (2004), Sun et al. (2009), Gipp et al. (2009), Liao et al. (2010), Kuo and Zhang (2012), Wu et al. (2012), Tsuji et al. (2012), Yang and Lin (2013), Kang and Choi (2011), Patton et al. (2012), Whitney and Schiff (2006), Renda and Straccia (2002), McNee et al. (2002), Pham et al. (2011), Yuan et al. (2011), Yoshikane and Itsumura (2013), Rocha (2001), Rao and Talwar (2011), Wilensky (2002), Aittola et al. (2003), Luo et al. (2010), Pagonis and Clark (2010), Serrano-Guerrero et al. (2011), Yang (2010), Popa et al. (2008)
The researchers have cited other researchers' definitions of context, e.g. day's definition	Trujillo et al. (2007), Rodriguez et al. (2009), Hwang et al. (2010), Krafft et al. (2008), Chen and Yang (2010), Kapoor et al. (2007), Andre Vellino & Zeber. (2007)
The researchers have presented a self-definition of context	Basu et al. (2011), Herrera-Viedma et al. (2008), Cheng Li et al. (2008), Amini et al. (2011), Martínez et al. (2010), Wu et al. (2012), Bollen and Van de Sompel (2006), De Giusti et al. (2010), Yang and Yun (2010), He et al. (2010), Yang et al. (2007)
The researchers have interviewed users or distributed questionnaires	Middleton et al. (2004), Wang et al. (2004), McNee et al. (2006), Wakeling (2012), Dehghani et al. (2011)
The researchers have not mentioned anything	(André Vellino, 2010), Webster et al. (2004), Tsai and Chen (2008), Nakagawa and Ito (2002), Middleton et al. (2002), Hwang et al. (2003), Konstan et al. (2005), Lopes et al. (2008), Luo et al. (2009), Liao et al. (2010), Herlocker et al. (2012), Carlos Porcel et al. (2009), Morales-del-Castillo et al. (2009), Geyer-Schulz et al. (2003b), Renda and Straccia (2002), Zarrinkalam and Kahani (2013), Steinberg et al. (2010), Pennock et al. (2000), Wang and Shao (2004), Geyer-Schulz et al. (2003a)

Overall, the results of this review showed that the majority of studies have applied classic approaches; however, there is no in-depth evaluation of both accuracy of recommendations and contextual information (Adomavicius & Jannach, 2013). Furthermore, systematic evaluation and comparison of different contextual methods, including pre-filtering, post-filtering and contextual modelling methods for generating appropriate recommendations have not been done in many studies. Therefore, a thorough search needs to be conducted in a scholar domain in order to explore which contextual method deals with unresolved issues more than other existing methods (Panniello, Tuzhilin, & Gorgoglione, 2012).

5.3. How has the relevance of contextual information on recommendations for an academic domain been understood by researchers before applying it?

The last question of this review addresses the way in which researchers have understood the relevancy of contextual information as expressed below. The importance of this question is intensified when researchers in the field of context awareness are unanimous that context is an ill-defended concept (Adomavicius & Jannach, 2013; Bazire & Brézillon, 2005) and emphasised that understanding context before using it in any application is very crucial (Bazire & Brézillon, 2005); since the notion and incorporation of context into recommendations may fluctuate within different circumstances and various domains, it implicitly challenges the studies that exploit contextual data without understanding contextual information and considering the influence of such information. Besides, user attributes in regard to contextual information may vary from what has been planned by the application designers (Yuan, 2014). Therefore, it is important to explore how relevant contextual information has been understood for recommending in a scholar domain and whether contextual information employed in scholarly RSs are relevant contexts. We managed to find the answer in the course of writing this review paper.

The results showed that past studies on RSs in DLs have captured the relevancy of contextual information on recommendations through five ways as shown in Table 6. The majority of studies employed contextual information based on data obtained from past studies in the same area; meanwhile, only a few studies performed separate investigation such as interview with users to explore the relevant contextual information from the users' point of view.

Based on the literature review, the majority of context-aware recommender systems have been designed and even evaluated with the assumption that users' context is fixed; this does not need to be addressed in a particular domain as the existing definitions of context have been cited frequently in many context-aware publications. The most cited definition of context has been provided by Abowd et al. (1999) where the context is defined as "any information that can be used to characterise the situation of an entity". They recognised four context categories, including identity, location, status and time; "identity" is the most popular among all the categories. For example, using user profile information has been considered as a main source of personalised recommendation filtering (Tejeda-Lorente et al., 2013) while the effectiveness of other contextual information such as user emotional states has been rarely contemplated in creating scholarly recommendations. However, some studies attempted to explain context and present new definitions with regard to an academic domain. However, the proposed definitions are not based on comprehensive research of the concept of context in a scholar domain. Hence, there is huge potential for this area to be the focus for further research not only in scholar context-aware applications but also for various applications.

6. Discussion and recommendations

Scholar recommender systems are employed to facilitate the process of information seeking for users. Incorporating contextual information in recommender systems is an effective approach to create more accurate and relevant recommendations. In this paper, we first discuss the concept of context and contextual approaches; we then examined 82 papers published on scholarly recommender systems from the years 2001 to 2013 by using the Kitchenham systematic review methodology in order to identify contextual information and methods used for making scholarly recommendations as well as the way researchers understood and used relevant contextual information in a scholar domain.

With the advent of context in computer science areas, many researchers have started to improve classical recommendations by incorporating contextual information such as time, location, weather, user current goals, user mood, activity, physical conditions, presence of other people, and the type of the device through which the recommendation is consumed (Adomavicius & Jannach, 2013; Adomavicius & Tuzhilin, 2011). In this regard, CARSs play an effective role in creating recommendations for two reasons (Baltrunas et al., 2012). First, they can present the situation and status of people, places, objects and devices in the environment (Asabere, 2013). Second, the importance of contextual information in accuracy of recommendations and RSs improvement has been strongly confirmed by many researchers in various areas such as mobile and ubiquitous computing, marketing, social networks and information systems (Adomavicius & Jannach, 2013). Nevertheless, identification of valid contextual information for different domains are challenges that should be considered (Yujie & Licai, 2010). Furthermore, the methods employed for making contextual recommendations have established a paradigm shift in the field of RSs (Adomavicius & Jannach, 2013).

Based on the findings of this review, we sorted and classified the contextual information derived from our review into three categories: user, document and environment contextual information. Although the main goal of this review is to collect exploited contextual information, it does not emphasise and accentuate using only contextual information in the process of providing scholarly recommendations. Hence, using too much contextual information leads to computational complexity and ambiguity in the system. This has an influence on the quality of recommendations (Yujie & Licai, 2010). Besides, it is not easy to find relevant contextual information for a specific domain like DLs. There is a tendency to find irrelevant contextual information, which may lead to false reasoning models and consequently irrelevant recommendations (Baltrunas et al., 2012). If appropriate contextual information is not applied, the performance accuracy of recommendations will be reduced (Adomavicius & Jannach, 2013). It requires formulating informed estimations about the influence of certain contextual information before collecting it in naturalistic environments (Baltrunas et al., 2012), which leads to diminution in the cost of real data acquisition (Rubens, Kaplan, & Sugiyama, 2011).

Additionally, users' behaviours vary in different domains, such as academic DLs and E-shopping. Therefore, the concept of context in RSs should be demarcated in their own domains where they are used by the end users (Woerndl & Schlichter, 2007). McNee (2006) argued that users estimate information needs and formulate judgment criteria in their minds. Hence, in order to build relevant, useful, and effective recommender systems, the validity of contextual information through the eyes of users ought to be evaluated.

Each type of classified contextual information consists of a few conditions or facets that are interrelated. For example, if an undergraduate student is searching for machine-learning methods, it might be inferred that the student does not have much pre-knowledge about the area and the advanced papers might not be the appropriate recommendations. On the other hand, there are a few conflicts between the conditions of contextual information; in the above example, if the student's pre-knowledge of machine-learning methods is strong despite being an undergraduate student, fundamental papers likely are inappropriate recommendations. Overall, the relations and conflicts of contextual information have not been included in our review. However, it is a crucial area that warrants further understanding and investigation so as to use contextual information effectively. Neuhold, Niederée, Stewart, Frommholz, and Mehta (2005) also confirmed that one of the biggest challenges in context representation or modelling is the identification of the right contextual information for the targeted service in a precise and traceable way.

Besides the above challenge, the problem of users' privacy is also very formidable since RSs rely on detailed personal data of the users' preferences for creation of accurate personalised recommendations (Jeckmans et al., 2013). A number of studies have stated that recommendations should be provided according to setting of users' personal privacy and permission to collect and use their data (Nika A. et al., 2011) so that when users interact with the DLs, they do not feel their privacy has been intruded. However, the problem of users' privacy protection in RSs has not been addressed in order to find applicable solutions. This area requires further research to discover new solutions.

According to our review on recommendation methods, contextual information was incorporated into recommendations mainly via classical approaches of collaborative filtering, content-based, knowledge-based and hybrid; among them, collaborative filtering was employed more than the other approaches. Recently, most of the digital libraries have switched to using web technologies such as linked data to represent the library data (Bojārs et al., 2013). Therefore, different approaches of building recommendations using linked open data standards such as RDFs, SPARQL and other semantic technologies can be addressed for making recommendations as a new generation of recommender systems. Furthermore, by using linked data, we can benefit from the rich source of data and overcome the problem of the data scarcity for creating recommendations (Heitmann & Hayes, 2010). Combination of contextual data by semantic technologies and representation of contextual linked data has the potential to add value to the context-aware recommender systems in DLs since the linked data create meaningful interlinks between data (Costabello, Villata, & Gandon, 2012) without human intervention and set up semantic links between objects in different data sources (Aftab, Afzal, and Khalid (2015), Bizer, Heath, & Berners-Lee, 2009).

The last issue with the contextual information is that a number of studies have assumed contexts do not change while others argue that contexts change. There are a limited number of studies that have detected a change in contextual information over time (Yujie & Licai, 2010). Herlocker et al. also confirms this issue requires more surveys to create intelligent recommendation approaches (Herlocker et al., 2012).

According to our review, we found that various recommendation approaches were employed for scholarly RSs. However, there is no contextual comprehensive approach to adapt the recommendations to the users' contexts. However, recently, most of the DLs use web technologies such as linked data to represent the library data (Bojārs et al., 2013). Therefore, different approaches to building recommendations using linked data should be addressed where similarities and relations between items in a database are identified by cataloguing, content analysis, keyword identification and tagging. Recommendations are then made based on semantic relations between the content of the items and the preferences that a user has expressed in the past (Ostuni et al., 2013).

In our review, we did not find any study that considers users' emotional states in creating scholarly recommendations. This might be an effective useful factor when users are in different emotional conditions such as anxiety, desperation, dissatisfaction and despair. Furthermore, few studies utilised the environment contextual information in making recommendations. For instance, there is no trace of using information such as noise level, brightness, temperature and weather in our review. Therefore, we recommend researchers in future studies to identify different scenarios where users' emotional states and environment contextual information are applicable to scholarly recommendations.

Overall, in order to make relevant recommendations, we need to be aware of users' situations in an academic domain and the problems users face. Context is a concept that needs to be investigated comprehensively in its own domain. Thus, the actual usage of context attributes is largely dependent on the application domain. In most of the reviewed studies, contextual information was analysed based on the definitions provided in past studies without any serious investigation on exploring accurate and relevant contextual information in the area of scholarly RSs. Therefore, it is critical to conduct an in-depth study on users' scholarly contexts to identify appropriate contextual information in scholarly domains and estimate their relevancies before building scholarly RSs. Furthermore, the concept of context is derived from humanity areas. Hence, it might be prudent to conduct a few studies that concentrate on users' contexts by using qualitative methods such as Ethnography, Sense Making, Grounded Theory, and Discourse Analysis; these methods aim to explore in-depth study of human behaviours in a particular domain and the reasons that lead to such behaviours.

In accordance with the results and insights turned out by this review, we propose a few research areas for further research. The suggestions are:

- Systematic comparison of the contextual approaches of pre-filtering, post-filtering and contextual modelling in a scholar recommender system in order to identify which one of them is more applicable for scholar recommendations versus classical approaches.
- Comprehensive research to gain a better understanding of scholar context notion and its users as well as the relations between them. For example, we did not find any study that covers user emotional states in creating scholarly recommendations; this is crucial since the user emotional status might overshadow the user preferences.
- Using qualitative research has a significant impact on recommendations as qualitative research methodologies can be very subjective when dealing with difficult situations and could have been biased by the researcher's perspective. Moreover, qualitative research methodologies are concerned with the opinions, experiences and feelings of individuals (Liamputtong, 2009).
- How context can be incorporated into linked data principles for providing recommendations in a digital library or other applications.
- Methods and experimental designs for evaluating contextual recommendations in scholar digital libraries. It can be accomplished for other domains such as marketing, tourism, and dining.
- Privacy concerns in scholar recommender systems and influences of user monitoring and controlling on recommending.
- How recommending approaches can encompass user long-term and short-term preferences and create proactive recommendations.

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