A Literature Review of Recommender Systems for the Cultural Sector

Nguyen Anh Khoa Dam[a] and Thang Le Dinh[b]
Department of Marketing and Information Systems, Université du Québec à Trois-Rivières, Trois-Rivières, Canada

Keywords: Recommender System, Cultural Sector, Business Analytics, Artificial Intelligence, SMEs/SMOs.

Abstract: Nowadays, organizations in the cultural sector have faced the problem of improving the discoverability of their products to meet the target objective regardless of the tremendous amount of information. In this respect, recommender systems have been proven to be the solution for enterprises, especially for cultural small and medium-sized organizations and enterprises (SMOs/SMEs), to enhance the discoverability of their products. This study aims at presenting a concept-centric literature review of recommender systems for cultural SMEs/SMOs to identify the current status-quo of the application in six cultural domains, including heritage and libraries, live performance, visual and applied arts, written and published works, audio-visual and interactive media, and sound recording. The finding of this paper reveals the adoption of recommender systems of cultural SMOs/SMEs is still in the early stage of maturity. The specific status-quo of recommender system adoption in each cultural domain is uncovered through the literature review. Other relevant aspects, which relate to data sources, data mining models, and algorithms, are also discussed in detail. Finally, the paper proposes future research directions to promote the application of artificial intelligence in general, and recommender systems, in particular, in the cultural sector.

1 INTRODUCTION

In the age of big data, the challenge of customers has changed from information shortage into information overload (Sassi, Mellouli, & Yahia, 2017). This stimulates the need of filtering out misleading information and efficiently searching for the right information (Ekstrand, Riedl, & Konstan, 2011; Schafer, Frankowski, Herlocker, & Sen, 2007; Wedel & Kannan, 2016). Accordingly, organizations and enterprises in the cultural sector face the problem of improving the discoverability of their products and services; hereafter called *cultural products*, to meet target profits regardless of the tremendous amount of information. The discoverability (Dasgupta et al., 2007) is defined as the ability of cultural products to be found by customers who search for them and to be recommended to those who are unaware of them.

In this respect, *recommender systems (RSs)* have been proven to be the solution for the cultural sector, especially for *small and medium-sized organizations (SMOs) and enterprises (SMEs)*, to enhance the discoverability of their products (Bartolini et al., 2016; Kabassi, 2013; A. Moreno, Valls, Isern, Marin, & Borràs, 2013). However, choosing and developing the right approach for RSs seem to be a challenge for most enterprises, especially in the case of SMOs and SMEs with limited resources (Ekstrand et al., 2011; Wedel & Kannan, 2016).

For this reason, this study aims at presenting a literature review on recommender systems in the cultural sector for SMEs/SMOs. Therefore, the primary objective of the study is to identify the current status-quo of the RS adoption in different domains of the cultural sector. Based on the primary objective, the second objective is to identify the relevant aspects, which need to be taken into account, relates to data sources, data mining models, and algorithms for recommender systems.

This paper is structured as follows. At first, the paper continues with the theoretical background. The research design, including the research process and classification framework, is also presented as the foundation to categorize articles in this literature review. Then the paper analyzes the reviewed articles with an in-depth discussion. Future research

[a] https://orcid.org/0000-0003-0928-8402
[b] https://orcid.org/0000-0002-5324-2746

Dam, N. and Dinh, T.
A Literature Review of Recommender Systems for the Cultural Sector.
DOI: 10.5220/0009337807150726
In *Proceedings of the 22nd International Conference on Enterprise Information Systems (ICEIS 2020) - Volume 1*, pages 715-726
ISBN: 978-989-758-423-7

directions are inferred from the discussion. Finally, the paper concludes with theoretical and practical contributions concerning this research stream.

2 BACKGROUND

The theoretical background begins with the different types of RSs, continues with the relations between RSs and customer experience and satisfaction, and ends with the adoption of RSs in the cultural sector.

Types of RSs. Recommender systems can be classified into three types: *Collaborative filtering (CF)*, *Content-based filtering (CB)*, and *Hybrid system* (Felício et al., 2016; Garcia, Sebastia, & Onaindia, 2011). A CF recommender system requires data on users' evaluation of purchase history to make suggestions (Lin, 2014). In contrast, CB recommender systems connect profiles of users' preferences with descriptions of relevant items (Mathew, Kuriakose, & Hegde, 2016). The hybrid systems integrate CF techniques with CB techniques or even with other techniques to optimize recommendations (Li, Xu, Wan, & Sun, 2018).

RSs and Customer Experience. Recommender systems play an important role in optimizing customer experience from finding to engaging with the products (Albadvi & Shahbazi, 2009; Barragáns-Martínez et al., 2010). The most significant function of RSs is to predict pertinent services or products based on users' preferences (Lu, Wu, Mao, Wang, & Zhang, 2015; H.-R. Zhang & Min, 2016). To put it concisely, RSs have two key functions: to predict and to recommend the most relevant service or products (Ekstrand et al., 2011; Schafer et al., 2007).

RSs and Customer Satisfaction. Recommender systems have been proven as a means to increase customer satisfaction, maintain a long-term relationship, and improve financial performance (Briguez et al., 2014; Siu, Zhang, Dong, & Kwan, 2013). Particularly, the applications of RSs produce prosperous results in the field of cultural heritage, tourism, and leisure activities (Bartolini et al., 2016; Kabassi, 2013; A. Moreno et al., 2013). Movie and music RSs built by Netflix and Yahoo have noticeably improved the financial performance of these enterprises (Christensen & Schiaffino, 2011; Jannach, Resnick, Tuzhilin, & Zanker, 2016).

RS Adoption in the Cultural Sector. Regardless of a wide range of adoption of RSs in the cultural sector, studies on such research stream scatter all over the literature. As a consequence, it is challenging to take an overview of the big picture of the RS adoption among different cultural domains. Even though CF systems are proven to be effective for the entertainment and cultural domain, they raise issues related to user engagement and accuracy as recommendations inferred from a community may not be precise for an individual member (Kabassi, 2013; Villegas, Sánchez, Díaz-Cely, & Tamura, 2018). Another drawback of the CF approach is the insufficient amount of data input, which is defined as the *cold start,* impedes many SMEs/SMOs at the early stage of adoption (Kabassi, 2013; Park, Kim, Choi, & Kim, 2012). On the other hand, CB systems face the problem of identifying algorithms for effectively matching common attributes between users and items (F. Deng, Ren, Qin, Huang, & Qin, 2018; Yao, Sheng, Segev, & Yu, 2013). The hybrid approach combing CF and CB has shown to outperform (van Capelleveen, Amrit, Yazan, & Zijm, 2019); yet, it requires a certain level of investment for information technology (IT) infrastructure which can be an obstacle for most SMEs/SMOs with financial constraints (Barragáns-Martínez et al., 2010; Park et al., 2012; Yao et al., 2013).

3 RESEARCH DESIGN

3.1 Research Process

As the nature of research on recommender systems and the cultural sector spreads over various databases, this paper builds its literature review from a wide range of academic sources such as Science Direct, Emerald, Business Source Premier, EBSCOhost, ProQuest, Google Scholars, and IEEE/IEE Library (Park et al., 2012). The search process is conducted through different descriptors: "recommender systems", "recommendation systems", "cultural domain", "cultural sector", "cultural heritage", "movie recommender", "music recommend*", "book recommend*", "image recommend*". Then more than 500 articles were screened based on abstracts, structure, and content. As the paper focuses on SMEs/SMOs, articles with relevant content are primarily chosen. Considering the limited number of articles for cultural SMEs/SMOs, the search was expanded to cultural organizations in general to ensure the broad literature review. However, the content of 69 selected articles is screened with the attention on the data mining models and IT infrastructure, which are applicable for SMEs/SMOs. These selected articles are from top Management and Information Systems journals such as Expert Systems

with Applications, Decision Support Systems, Knowledge-Based System, Decision Support Systems, IEEE, Information Sciences. These journals are also listed in the Scimago Journal & Country Rank in 2018.

Table 1: Distribution of articles by journal titles.

Journal Title	No	%
Expert Systems with Applications	17	24.6 %
IEEE	11	15.9%
Information Science	3	4.3%
Knowledge-Based System	6	8.7%
Decision Support Systems	4	5.8%
Neuro Computing	2	2.9%
Others	26	37.7%
Total	**69**	**100%**

According to Table 1, the number of relevant articles comes from Expert Systems with Applications (24.6%), followed by IEEE (15.9%) and Knowledge-Based System (8.7%). During the searching process, the forward and backward search techniques are implemented to ensure that the review of 69 chosen articles can represent the literature of this domain. Therefore, the paper can demonstrate its validity and reliability as a literature review.

The 69 reviewed articles are also categorized by years of publication (Figure 1). The period of a decade is chosen to examine the status quo and trends of research in this field. It is noticeable that the number of articles considerably increases compared to the past 10 years. There is a substantial increase in 2016 and 2018. This indicates the interests of scholars in the application of RSs in the cultural sector.

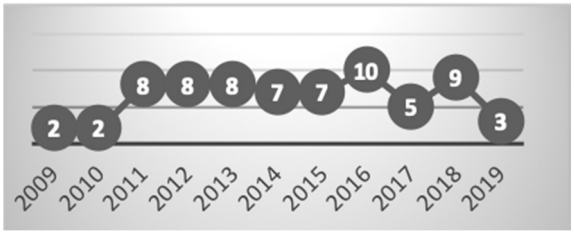

Figure 1: Distribution of articles by years of publication.

3.2 Classification Framework

The classification framework for recommender systems in the cultural sector consists of different domains and types of recommender systems. This study is based on the previous study of Park et al. (2012) whose objective is also to find out the trend of RS adoption in various application fields. Accordingly, the paper classifies reviewed articles into six cultural domains and three types of recommender systems. The classification of the literature review is introduced in Figure 2. A detailed description of the framework is presented in the next part of this paper.

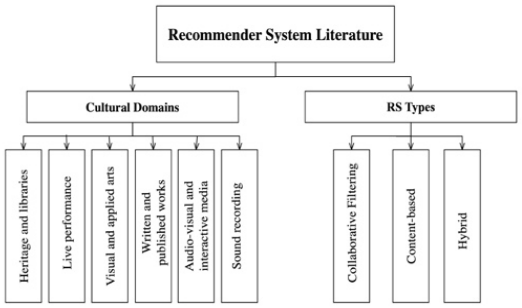

Figure 2: A classification framework.

Classification of Cultural Domains. Regarding the classification of the cultural domains, the paper classifies research articles based on the six domains of the cultural sector according to the *Canadian Framework for Culture Statistics* (Canada, 2011). These domains are Heritage and libraries, Live performance, Visual and applied arts, Written and published works, Audio-visual and interactive media, and Sound recording. The *Heritage and libraries domain* consists of definable related industries, products, and occupations associated with archives, libraries, cultural heritage, and natural heritage. The *Live performance domain* covers activities concerning the performing arts of theatre, artists, and multidisciplinary events (e.g.: celebrations and festivals). The *visual and applied arts domain* contains the following sub-domains: original visual art (e.g.: paintings, sculptures), art reproductions (copies of original visual arts), photography, and crafts. The *written and published works domain* symbolizes different kinds of publications, including books, periodicals, newspapers, and other published works. The *audio-visual and interactive media domain* is divided into three categories: film and video, broadcasting (e.g.: radio, television, the Internet) and interactive media (e.g.: online games). The *Sound recording domain* represents sound recording and music publishing.

Various RSs have been developed in different domains of the cultural sector. The cultural heritage domain has witnessed the evolution of various versions of RSs in enhancing access to museums, galleries, and other historic places. In the domains of movies, music, and books, several RSs were built to help users find relevant items. However, it is

challenging to find studies, which discuss RSs for several different domains of the cultural sector.

Classification of RSs. As mentioned in previous sections, recommender systems can be classified generally into three specific types: collaborative filtering, content-based filtering, and hybrid system. Classifying the selected articles with types of recommender systems indicates the current status and trends of applications of such systems in different domains of the cultural sector. The identification of RS types also gives an idea of algorithms as well as required IT architecture for developing and exploiting the system. Therefore, it is significant to classify the literature review based on the three types of recommender systems. A more detailed description of the three RSs is also presented as follows:

(1) *Collaborative filtering (CF) recommender systems* are based on users' evaluation of a set of items such as songs, movies, images (Barragáns-Martínez et al., 2010; Schafer et al., 2007). Under this approach, users who share similar opinions on specific items tend to have the same idea on other issues (Barragáns-Martínez et al., 2010; Bobadilla, Ortega, Hernando, & Gutiérrez, 2013). Collaborative filtering recommender systems make predictions to a specific user regarding the fact that these systems use information extracted from many users (Schafer et al., 2007; Wedel & Kannan, 2016).

(2) *Content-based filtering (CB) recommender systems* match profiles of users' preferences with descriptions of relevant items (Barragáns-Martínez et al., 2010; Yao et al., 2013). In these systems, algorithms recommend similar items that a user used to like or interact with. Three components of content-based filtering recommender systems are profiles of users' preferences, item descriptions, and item comparison to user profiles (Barragáns-Martínez et al., 2010). Content-based filtering recommender systems seem to prevail today due to the vast content on social media (Barragáns-Martínez et al., 2010; Bobadilla et al., 2013).

(3) *Hybrid recommender systems* combine content-based filtering with collaborative filtering or other approaches to take advantage of each technique (Barragáns-Martínez et al., 2010; Bobadilla et al., 2013). The limitation of CF recommender systems related to the lack of information about user's behaviors can be solved by the functionality of the CB approach (Albanese, d'Acierno, Moscato, Persia, & Picariello, 2011). On the contrary, the issue faced CB recommender systems are over-specialization, which only focuses on similar items to user preferences and ignores "different" items although a user might want to try something new (Borràs, Moreno, & Valls, 2014). As a matter of fact, the functionality of the CF approach can overcome this limitation (Kazienko & Kolodziejski, 2006). The hybrid approach is proved to outperform the CF and CB ones (Yao et al., 2013).

4 LITERATURE REVIEW

Articles are categorized based on the classification framework for recommender systems in the cultural sector (Table 2). The degree of coverage of all the articles related to each sub-category is noted with three levels: highly covered (***), moderately covered (**), and slightly covered (*) (Rickenberg, Neumann, Hohler, & Breitner, 2012).

The reviewed articles are ordered in a concept-centric way instead of being arranged based on author names or year of publication (Webster & Watson, 2002). Accordingly, there are two key concepts: cultural domains and RS types. On the horizontal dimension of Table 2, the concepts are broken down into units of analysis (Webster & Watson, 2002). The "cultural domains" concept consists of six units of analysis whereas the "RS types" concept covers three units. On the vertical dimension of Table 2, the cluster analysis approach (Rickenberg et al., 2012) is applied to group similar articles belonging to the same cultural domain. Reviewing the paper through vertical clusters with horizontal units of analysis reveals the relationships and coherency among articles.

Cultural Domains. The number of reviewed articles scatters over the six cultural domains as follows: heritage and libraries (23), live performance (3), visual and applied arts (11), written and published works (18), audio-visual and interactive media (30), and sound recording (28). Each cultural domain is considered as a unit of analysis in which the degree of intensity is calculated as the weighted total based on the extent of coverage such as highly covered (***x3), moderately covered (**x2), and slightly covered (*x1) (Rickenberg et al., 2012). Compared to the total score – the total number of articles discussing the topic, the weighted total will better inform the significance and trends of each unit of analysis.

Based on Table 2, recommender systems catch the most attention in the domain of audio-visual and interactive media with the highest intensity (70). The application of recommender systems in the domain of heritage and libraries keeps the second place with the level of high intensity (59). However, the number of articles discussing this domain (23) is less than those in the domain of music (28). Only a small portion of

the reviewed articles deals with recommender systems in the domains of visual and applied arts (11) and written and published works (18). The literature scarcely discusses the application of RSs for live performance, including performing art, festivals, and celebrations.

Table 2: Classification of the most relevant articles.

	Cultural Domains						**RS Types**		
	Heritage & libraries	Live performance	Visual & applied arts	Works	Media	Sound recordings	Collaborative filtering	Content-based	Hybrid
Albanese et al. (2011a)	***						*	*	***
Chianese et al. (2013)	***								***
Albanese et al. (2011b)	***		**				**	**	***
Borràs et al. (2014)	***						***	***	***
Bartolini et al. (2013)	***								***
Bartolini et al. (2016)	***						*	*	***
Kabassi (2013)	***								***
Moreno et al. (2013)	***						**	**	***
Cuomo et al. (2015)	***								**
Chianese and Piccialli (2016)	***								***
Garcia et al. (2011)	***							*	***
Siu et al. (2013)	***	*	*	*	*	*			
Portugal et al. (2018)	*	*	*	*	*	*	**	**	**
Villegas et al. (2018)	*			*	**	**	**	**	**
Champiri et al. (2015)	***			*	**		***	***	***
Noguera et al. (2012)	***						**	*	***
Park et al. (2012)	*	*	*	*	*	*	**	**	*
Umanets et al. (2014)	***						*	*	***
Yang and Hwang (2013)	***						*	***	
Ardissono et al. (2012)	***						**	**	**
Sassi et al. (2017)	***			*	**	**	**	**	**
Deng et al. (2018)			***				**	**	***
Sanchez et al. (2012)			***				***	***	***
Zhang et al. (2017)			***				***		
Sejal et al. (2016)			***					***	
Felício et al. (2016)			***						***
Tkalcic et al. (2012)			***					***	
Lin (2014)				**	*	*	***		
Albadvi and Shahbazi (2009)				**		**	*	*	***
Bedi and Agarwal (2011)				***					***
Bedi and Vashisth (2014)				***					***
Zhou (2010)				***					***
Hariadi and Nurjanah (2017)				***					***
Alharthi et al. (2018)				***			*	***	***
Núñez-Valdéz et al. (2012)				***			*	*	*
Nirwan et al. (2016)				***					***
Mathew et al. (2016)				***			***	***	***

Table 2: Classification of the most relevant articles (cont.).

	Cultural Domains						RS Types		
	Heritage & libraries	Live performance	Visual & applied arts	Works	Media	Sound recordings	Collaborative filtering	Content-based	Hybrid
Colombo-Mendoza et al. (2015)					***				***
Katarya and Verma (2017)					***		***		***
Li et al. (2018)					***		**		***
Koren et al. (2009)					***	*	***	*	
Ekstrand et al. (2011)					***	*	***	*	*
Kim et al. (2011a)					***		***	*	*
Carrer-Neto et al. (2012)					***		*	*	***
Eirinaki et al. (2018)	*			*	**	*	***	*	*
Beel et al. (2013)					**	*			
Kim et al. (2011b)					*	*	***	*	
van Capelleveen et al. (2019)					*				***
Barragáns-Martínez et al. (2010)					***	*	**		***
Bobadilla et al. (2013)					***	**	**	**	***
Jannach et al. (2016)					***	*	**	*	
Hu et al. (2019)					***		***		
Moreno et al. (2016)					***		***		***
Briguez et al. (2014)					***				***
Zhang and Min (2016)					***	*			***
Pereira and Hruschka (2015)					***		**		***
Viktoratos et al. (2018)					**		*	*	***
Hyung et al. (2014)						***			***
Lee et al. (2017)						***	***		
Lu et al. (2015)	*		*	*	***	***	**	**	***
Christensen and Schiaffino (2011)					***	***	*		***
Bauer and Nanopoulos (2014)					*	**	***	*	*
Kaminskas and Ricci (2012)						***	**	**	***
Andjelkovic et al. (2019)						***			***
Zheng et al. (2018)						***	***		***
Sánchez-Moreno et al. (2016)						***	***		
Deng et al. (2015)						***	***		***
Horsburgh et al. (2015)						***			***
Liu and Chen (2018)						***	***		
Total	23	3	11	18	30	28	46	35	55
Weighted total:	59	3	24	36	70	55	102	62	148
Notation: Highly covered: ***x3; Moderately covered: **x2; Slightly covered: *x1									

Types of RSs. The number of articles covering each unit of analysis, including collaborative filtering (46), content-based filtering (35), and hybrid (55) points out interesting facts. Accordingly, the hybrid approach receives the most attention from scholars with the highest intensity (148). This finding is also supported by previous studies (Umanets et al., 2014; van Capelleveen et al., 2019). Followed by the hybrid

approach is the collaborative filtering RS with a high intensity of 102. The content-based RSs catches the least attention of scholars with the low intensity (62).

5 DISCUSSION

This paper reviewed 69 academic articles to gain a comprehensive and in-depth insight into the current status of the applications of recommender systems in the cultural sector. The number of reviewed articles is selected from a broad range of scientific journals to demonstrate a multifaceted spectrum of scholars and opinions in this research field. Based on the research objectives, the discussion focuses on the application of RSs in the cultural domains and relevant aspects related to data sources, models and algorithms.

5.1 Applications of RSs

Even though the topic of RSs is traditional in the information system research; however, the application of RSs is an up-to-date research stream - especially in the cultural sector.

Audio-visual and Interactive Media, and Sound Recording Domains. The finding of this paper indicates that the applications of RSs dominate in the domain of audio-visual and interactive media, followed by the sound recording domain. This finding reaches an agreement with the previous studies regarding the blossom of many movies and music RSs (Andjelkovic et al., 2019; Katarya & Verma, 2017). Netflix's recommender system would be a salient example as it contributes more than 75% of the total movie downloads and rentals (Jannach et al., 2016). The most popular music recommender system with a significant impact on the music industry is Last.fm (Horsburgh et al., 2015; Zheng et al., 2018). The common goal of RSs in the movie and music RSs is to navigate and discover songs or movies and then share them with a specific user community (Eirinaki et al., 2018; Kaminskas & Ricci, 2012). Therefore, RSs in these two domains emphasize the significance of social networks (Carrer-Neto et al., 2012). Accordingly, hybrid RSs integrated with user-generated tags for social RSs seem to dominate these domains as they outperform CF and CB systems (Kim, Alkhaldi, et al., 2011; Pereira & Hruschka, 2015). Merging various techniques, hybrid RSs can improve user satisfaction and outperform other systems (Andjelkovic et al., 2019; Christensen & Schiaffino, 2011).

Heritage and Libraries Domain. In light of the heritage and libraries domain, the application of RSs serves two purposes: to recommend a destination for visits and to suggest a list of activities for visitors to enjoy such a destination (Garcia et al., 2011). To facilitate these purposes, RSs in this cultural domain often apply information technologies - for example, a mobile platform - to support on-site recommendations while users at those cultural sites can know what to do or where to go (Ardissono et al., 2012; Chianese et al., 2013). Location and activities-based RSs are mostly developed upon the content-based approach (Villegas et al., 2018). However, a user may not satisfy with all recommendations in which he or she shows an interest (Yang & Hwang, 2013). Therefore, collaborative filtering techniques are integrated to form a hybrid system. Hybrid RSs which combine multiple filtering techniques are the preferred choice in this domain (Umanets et al., 2014; van Capelleveen et al., 2019).

Live Performance Domain. Although the application of RSs in the live performance domain serves the same purposes as the heritage and libraries domain, very few RSs are developed and implemented. This can be explained by the occasional and short-term characteristics of performance, festivals, and celebrations. In this domain, investment in RSs may not yield profitable outcomes.

Written and Published Works Domain. RSs in this domain give prominence to the importance of trust for reliable recommendations (Bedi & Agarwal, 2011). Especially through the platform of Web and social networks, recommendations from users' opinions are rated by other users to ensure trustworthiness and avoid scams (Bedi & Vashisth, 2014; Zhou, 2010). The hybrid approach still dominates in developing RSs for books, periodicals, and newspapers (Hariadi & Nurjanah, 2017). However, it is noticeable that a significant number of book recommendations are based on the CB approach (Zhou, 2010). This is rationalized by the fact that the CB can avoid the cold start's problem of lacking data on new items from the CF approach (Alharthi et al., 2018). CB systems do not rely on user ratings as they make recommendations based on metadata of items. Metadata reveals attributes of items related to unique identifiers, years of publication, description, legal aspects, enrichment, technicality, contextual or demographic information (Alharthi et al., 2018). Structured and standardized metadata will facilitate the discoverability of cultural contents via RSs (Andjelkovic et al., 2019; Eirinaki et al., 2018).

Visual and Applied Arts Domain. Only a small proportion of the literature view discusses the applications of RSs in the domain of visual and applied arts. The hybrid approach, which is considered the most optimal can improve up to 90% of recommendation quality (F. Deng et al., 2018; Tkalcic et al., 2012). Hybrid RSs take advantage of data on users' visual perception from the content-based approach to overcome the problem of recommendation reliability of collaborative filtering techniques (Felício et al., 2016). Metadata on users' visual perception will function as a source of contextual information (Tkalcic et al., 2012); therefore, the problem of different degrees of affinity among users with similar attributes can be handled (Felício et al., 2016; Sanchez et al., 2012). The challenges of aesthetics taste dispersion and undefined visual tastes of content-based techniques can also be overcome through recommendation techniques inferred from a user community of the CF approach (Sanchez et al., 2012).

5.2 Data Sources

Recommender systems are considered as the significant application of knowledge management to recommend user's relevant products, services, or contents (Park et al., 2012). Main data sources for recommender systems are internal databases, websites, social media, and integrated devices/sensors (Fan, Lau, & Zhao, 2015; Park et al., 2012). Data sources for RSs have changed along with the prosperity of the era of information overload.

The first generation of RSs are built from website data on purchases, users' demography and preference (Bobadilla et al., 2013). In the digital age, user data can be initially cookies and server logs (Chen, Chiang, & Storey, 2012). Enterprises can obtain customer clickstream data logs on visit frequency, viewed items, and visit time to demystify customer behaviors (Fan et al., 2015; Park et al., 2012). Users' demography and preference data reveal information on age, gender, preferences, cultures, lifestyle, purchasing power, shopping behaviors, customs and habits of potential and existing customers (Albanese, d'Acierno, et al., 2011; Dam, Le Dinh, & Menvielle, 2019). Therefore, the first generation of RSs will allow enterprises to personalize recommendations for each customer through data from clickstreams, customer profiles, mobile call records, and transactions for better customer satisfaction (Kabassi, 2013; Park et al., 2012).

The second generation of recommender systems is built from social media data such as friends, likes, followers, followed, tweets, and posts, etc. (Bobadilla et al., 2013; Ma, Zhou, Liu, Lyu, & King, 2011). Social intelligence extracted from user-contributed data on social media can help enterprises in designing new products, implementing marketing strategies, and recommend relevant contents for online users (Abbasi, Chen, & Salem, 2008; Archak, Ghose, & Ipeirotis, 2011; Lau, Li, & Liao, 2014). The real-time property of social intelligence along with its subjectivity in a specific context is significantly believed to be more trustworthy, updated, and reliable compared to traditional sources of information (Abbasi et al., 2008; Lau et al., 2014). Due to these characteristics, data from social media can improve the functions of prediction and recommendation of recommender systems (Bobadilla et al., 2013; Ma et al., 2011). Mining user-generated content and web content will allow enterprises not only to develop suitable products for customer needs but also to predict a set of relevant products and recommend the top ones to the right customers (Payne & Frow, 2005; Rygielski, Wang, & Yen, 2002). Therefore, the applications of recommender systems have emerged in various fields, including music, books, shopping, applications, TV programs, e-learning material, and web search (Bobadilla et al., 2013; Park et al., 2012). One of the challenges faced this generation is to integrate and consolidate the different data sources (Le Dinh & Nguyen-Ngoc, 2010).

The third generation of recommender systems is built from data from integrated devices/sensors (RIFD, real-time health, location-based, or weather devices, etc.) as the trends of the Internet of Things (Bobadilla et al., 2013). In particular, location-based data which can be traced through mobile devices with GPS, Wi-Fi, GSM, or Bluetooth, vehicles with GPS, smart cards (bank cards or transportation cards), floating sensors (devices with radio frequency identification), check-in from social networks, can offer real-time property for recommender systems (Pan et al., 2013; Scellato, Noulas, & Mascolo, 2011). These integrated devices /sensors, which represent the Internet of Things, are catching attention in building recommender systems (Bobadilla et al., 2013; Ma et al., 2011).

5.3 Data Mining Models and Algorithms

Different data mining models such as the association, classification, clustering, and regression are commonly used for building recommender systems (Adomavicius & Tuzhilin, 2005). Association models are widely used in many RSs with various data

mining techniques such as k-Nearest Neighbor, Bayesian classifiers, association rules, decision trees, link analysis, neural networks, and linear regression (Adomavicius & Tuzhilin, 2005; Park et al., 2012). As one of the most popular techniques, k-Nearest Neighbor (k-NN) identifies users with similar behaviors through their preference ratings and filters top recommendations are most likely to be purchased (Albadvi & Shahbazi, 2009). Other common data mining techniques to develop RSs involve association rules and link analysis (Park et al., 2012). On the other hand, heuristics, clustering, and association models are often applied to make recommendations related to promotional strategies (Park et al., 2012). Recommender systems will be able to promote suitable products for target customers, especially for movies and shopping industries (Payne & Frow, 2005; Rygielski et al., 2002). To sum up, the most common data mining techniques to build recommender systems are k-Nearest Neighbor, association rules, and link analysis (Koren et al., 2009; Park et al., 2012).

6 CONCLUSIONS

To facilitate the application of recommender systems for small and medium-sized organizations and enterprises (SMOs/SMEs) in the cultural domain, this paper presents an in-depth literature review of 69 academic articles to gain an understanding of the current status-quo and related aspects on data sources, data mining models and algorithms. The concept-centric approach along with the cluster analysis is applied to categorize all the selected articles to examine the coherence and relationships among them. The results of this study have made important theoretical and practical contributions.

The findings of this paper reveal the status of the application of recommender systems in different domains of the cultural sector. Despite the limited number of articles in this research stream, articles discussing the applications of RSs in each cultural domain scatter all over the literature. Hardly any paper has categorically synthesized and reviewed the literature of all six cultural domains, including heritage and libraries, live performance, visual and applied arts, written and published works, audio-visual and interactive media, and sound recording. Therefore, this paper can be considered as the pioneered literature review, which fulfills a significant gap in the cultural sector. Another theoretical contribution of this paper relates to the application of information systems in the reflection of recommender systems for cultural SMEs/SMOs. Considering the fact that there is little research, which links the two different domains - information systems and the cultural sector, the proposed classification framework can be a reference for researchers to deepen their studies and enrich literature.

In terms of practical contributions, the literature review will give cultural SMEs/SMOs an idea on what type of recommender systems would suit their needs. The paper also foresees the relevant issues related to the data sources, algorithms, levels of user engagement, and requirements for IT infrastructure. The proposed future research directions also infer enterprises about state-of-the-art RSs. Catching up with the trend in the development of RSs will help enterprises better respond to their needs. Therefore, the paper will serve as a good starting point for managers who consider adopting a recommender system. The successful adoption of a recommender system would enhance the discoverability of cultural content and products for enterprises in the cultural sector. Without any doubt that cultural SMEs/SMOs which can take advantage of recommender systems can gain a competitive advantage in the fierce competition of the big data era.

At present, a conceptual framework for context-aware recommender systems is being developed. This framework will be experienced with a case study, which aims at developing a recommender system for a regional cultural development organization in Canada to promote the discoverability of the products and services of its members.

REFERENCES

Abbasi, A., Chen, H., & Salem, A. (2008). Sentiment analysis in multiple languages: Feature selection for opinion classification in Web forums. *ACM Transactions on Information Systems, 26*(3), 12.

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge & Data Engineering*(6).

Albadvi, A., & Shahbazi, M. (2009). A hybrid recommendation technique based on product category attributes. *Expert Systems with Applications, 36*(9), 11480-11488. doi:10.1016/j.eswa.2009.03.046

Albanese, M., d'Acierno, A., Moscato, V., Persia, F., & Picariello, A. (2011). *A multimedia semantic recommender system for cultural heritage applications.* Paper presented at the 2011 IEEE Fifth International Conference on Semantic Computing.

Albanese, M., d'Acierno, A., Moscato, V., Persia, F., & Picariello, A. (2011). A novel strategy for recommending multimedia objects and its application

in the cultural heritage domain. *International Journal of Multimedia Data Engineering Management Science, 2*(4), 1-18.

Alharthi, H., Inkpen, D., & Szpakowicz, S. (2018). A survey of book recommender systems. *Journal of Intelligent Information Systems, 51*(1), 139-160.

Andjelkovic, I., Parra, D., & O'Donovan, J. (2019). Moodplay: interactive music recommendation based on artists' mood similarity. *International Journal of Human-Computer Studies, 121*, 142-159.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science, 57*(8).

Ardissono, L., Kuflik, T., & Petrelli, D. (2012). Personalization in cultural heritage: the road travelled and the one ahead. *User modeling user-adapted interaction, 22*(1-2), 73-99.

Barragáns-Martínez, A. B., Costa-Montenegro, E., Burguillo, J. C., Rey-López, M., Mikic-Fonte, F. A., & Peleteiro, A. (2010). A hybrid content-based and item-based collaborative filtering approach to recommend TV programs enhanced with singular value decomposition. *Information sciences, 180*(22), 4290-4311.

Bartolini, I., Moscato, V., Pensa, R. G., Penta, A., Picariello, A., Sansone, C., & Sapino, M. L. (2013). *Recommending multimedia objects in cultural heritage applications.* Paper presented at the International Conference on Image Analysis and Processing.

Bartolini, I., Moscato, V., Pensa, R. G., Penta, A., Picariello, A., Sansone, C., & Sapino, M. L. (2016). Recommending multimedia visiting paths in cultural heritage applications. *Multimedia tools applications, 75*(7), 3813-3842.

Bauer, J., & Nanopoulos, A. (2014). Recommender systems based on quantitative implicit customer feedback. *Decision Support Systems, 68*, 77-88.

Bedi, P., & Agarwal, S. K. (2011). *Managing security in aspect oriented recommender system.* Paper presented at the 2011 International Conference on Communication Systems and Network Technologies.

Bedi, P., & Vashisth, P. (2014). Empowering recommender systems using trust and argumentation. *Information sciences, 279*, 569-586.

Beel, J., Langer, S., Genzmehr, M., Gipp, B., Breitinger, C., & Nürnberger, A. (2013). *Research paper recommender system evaluation: a quantitative literature survey.* Paper presented at the Proceedings of the International Workshop on Reproducibility and Replication in Recommender Systems Evaluation.

Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-Based Systems, 46*, 109-132. doi:10.1016/j.knosys.2013.03.012

Borràs, J., Moreno, A., & Valls, A. (2014). Intelligent tourism recommender systems: A survey. *Expert Systems with Applications, 41*(16), 7370-7389.

Briguez, C. E., Budan, M. C., Deagustini, C. A., Maguitman, A. G., Capobianco, M., & Simari, G. R. (2014). Argument-based mixed recommenders and their application to movie suggestion. *Expert Systems with Applications, 41*(14), 6467-6482.

Canada, S. (2011). Conceptual framework for culture statistics 2011. In: Minister of Industry Ottawa, ON.

Carrer-Neto, W., Hernández-Alcaraz, M. L., Valencia-García, R., & García-Sánchez, F. (2012). Social knowledge-based recommender system. Application to the movies domain. *Expert Systems with Applications, 39*(12), 10990-11000.

Champiri, Z. D., Shahamiri, S. R., & Salim, S. S. B. (2015). A systematic review of scholar context-aware recommender systems. *Expert Systems with Applications, 42*(3), 1743-1758.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*, 1165-1188.

Chianese, A., Marulli, F., Piccialli, F., & Valente, I. (2013). *A novel challenge into multimedia cultural heritage: an integrated approach to support cultural information enrichment.* Paper presented at the 2013 International Conference on Signal-Image Technology & Internet-Based Systems.

Chianese, A., & Piccialli, F. (2016). A smart system to manage the context evolution in the Cultural Heritage domain. *Computers Electrical Engineering, 55*, 27-38.

Christensen, I. A., & Schiaffino, S. (2011). Entertainment recommender systems for group of users. *Expert Systems with Applications, 38*(11), 14127-14135.

Colombo-Mendoza, L. O., Valencia-García, R., Rodríguez-González, A., Alor-Hernández, G., & Samper-Zapater, J. J. (2015). RecomMetz: A context-aware knowledge-based mobile recommender system for movie showtimes. *Expert Systems with Applications, 42*(3), 1202-1222.

Cuomo, S., De Michele, P., Galletti, A., & Piccialli, F. (2015). *A cultural heritage case study of visitor experiences shared on a social network.* Paper presented at the 2015 10th International Conference on P2P, Parallel, Grid, Cloud and Internet Computing (3PGCIC).

Dam, N. A. K., Le Dinh, T., & Menvielle, W. (2019). Marketing Intelligence From Data Mining Perspective – A Literature Review. *International Journal of Innovation, Management and Technology*.

Dasgupta, A., Ghosh, A., Kumar, R., Olston, C., Pandey, S., Tomkins, A., . . . Tomkins, A. (2007). *The discoverability of the web.* Paper presented at the Proceedings of the 16th international conference on World Wide Web.

Deng, F., Ren, P., Qin, Z., Huang, G., & Qin, Z. (2018). Leveraging Image Visual Features in Content-Based Recommender System. *Scientific Programming, 2018*.

Deng, S., Wang, D., Li, X., & Xu, G. (2015). Exploring user emotion in microblogs for music recommendation. *Expert Systems with Applications, 42*(23), 9284-9293.

Eirinaki, M., Gao, J., Varlamis, I., & Tserpes, K. (2018). Recommender systems for large-scale social networks: A review of challenges and solutions. *Future Generation Computer Systems*.

Ekstrand, M. D., Riedl, J. T., & Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations Trends in Human–Computer Interaction, 4*(2), 81-173.

Fan, S., Lau, R. Y. K., & Zhao, J. L. (2015). Demystifying Big Data Analytics for Business Intelligence Through the Lens of Marketing Mix. *Big Data Research, 2*(1), 28-32. doi:10.1016/j.bdr.2015.02.006

Felício, C. Z., De Almeida, C. M., Alves, G., Pereira, F. S., Paixao, K. V., De Amo, S., & Barcelos, C. A. (2016). *Vp-rec: A hybrid image recommender using visual perception network.* Paper presented at the 2016 IEEE 28th International Conference on Tools with Artificial Intelligence (ICTAI).

Garcia, I., Sebastia, L., & Onaindia, E. (2011). On the design of individual and group recommender systems for tourism. *Expert Systems with Applications, 38*(6), 7683-7692.

Hariadi, A. I., & Nurjanah, D. (2017). *Hybrid attribute and personality based recommender system for book recommendation.* Paper presented at the 2017 International Conference on Data and Software Engineering (ICoDSE).

Horsburgh, B., Craw, S., & Massie, S. (2015). Learning pseudo-tags to augment sparse tagging in hybrid music recommender systems. *Artificial Intelligence, 219*, 25-39.

Hu, Y., Xiong, F., Lu, D., Wang, X., Xiong, X., & Chen, H. (2019). Movie collaborative filtering with multiplex implicit feedbacks. *Neurocomputing*.

Hyung, Z., Lee, K., & Lee, K. (2014). Music recommendation using text analysis on song requests to radio stations. *Expert Systems with Applications, 41*(5), 2608-2618.

Jannach, D., Resnick, P., Tuzhilin, A., & Zanker, M. (2016). Recommender systems—beyond matrix completion. *Communications of the ACM, 59*(11), 94-102.

Kabassi, K. (2013). Personalisation systems for cultural tourism. In *Multimedia services in intelligent environments* (pp. 101-111): Springer.

Kaminskas, M., & Ricci, F. (2012). Contextual music information retrieval and recommendation: State of the art and challenges. *Computer Science Review, 6*(2-3), 89-119.

Katarya, R., & Verma, O. P. (2017). An effective collaborative movie recommender system with cuckoo search. *Egyptian Informatics Journal, 18*(2), 105-112.

Kazienko, P., & Kolodziejski, P. (2006). Personalized Integration of Recommendation Methods for E-commerce. *IJCSA, 3*(3), 12-26.

Kim, H.-N., Alkhaldi, A., El Saddik, A., & Jo, G.-S. (2011). Collaborative user modeling with user-generated tags for social recommender systems. *Expert Systems with Applications, 38*(7), 8488-8496.

Kim, H.-N., El-Saddik, A., & Jo, G.-S. (2011). Collaborative error-reflected models for cold-start recommender systems. *Decision Support Systems, 51*(3), 519-531.

Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *Computer*(8), 30-37.

Lau, R. Y. K., Li, C., & Liao, S. S. Y. (2014). Social analytics: Learning fuzzy product ontologies for aspect-oriented sentiment analysis. *Decision Support Systems, 65*, 80-94. doi:10.1016/j.dss.2014.05.005

Le Dinh, T., & Nguyen-Ngoc, A. V. (2010). *A conceptual framework for designing service-oriented inter-organizational information systems.* Paper presented at the Proceedings of the 2010 Symposium on Information and Communication Technology.

Lee, W.-P., Chen, C.-T., Huang, J.-Y., & Liang, J.-Y. (2017). A smartphone-based activity-aware system for music streaming recommendation. *Knowledge-Based Systems, 131*, 70-82.

Li, J., Xu, W., Wan, W., & Sun, J. (2018). Movie recommendation based on bridging movie feature and user interest. *Journal of computational science, 26*, 128-134.

Lin, Z. (2014). An empirical investigation of user and system recommendations in e-commerce. *Decision Support Systems, 68*, 111-124.

Liu, C.-L., & Chen, Y.-C. (2018). Background music recommendation based on latent factors and moods. *Knowledge-Based Systems, 159*, 158-170.

Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments. *Decision Support Systems, 74*(C), 12-32. doi:10.1016/j.dss.2015.03.008

Ma, H., Zhou, D., Liu, C., Lyu, M. R., & King, I. (2011). *Recommender systems with social regularization.* Paper presented at the Proceedings of the fourth ACM international conference on Web search and data mining.

Mathew, P., Kuriakose, B., & Hegde, V. (2016). *Book Recommendation System through content based and collaborative filtering method.* Paper presented at the 2016 International Conference on Data Mining and Advanced Computing (SAPIENCE).

Moreno, A., Valls, A., Isern, D., Marin, L., & Borràs, J. (2013). Sigtur/e-destination: ontology-based personalized recommendation of tourism and leisure activities. *Engineering Applications of Artificial Intelligence, 26*(1), 633-651.

Moreno, M. N., Segrera, S., López, V. F., Muñoz, M. D., & Sánchez, Á. L. (2016). Web mining based framework for solving usual problems in recommender systems. A case study for movies′ recommendation. *Neurocomputing, 176*, 72-80.

Nirwan, H., Verma, O. P., & Kanojia, A. (2016). *Personalized hybrid book recommender system using neural network.* Paper presented at the 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom).

Noguera, J. M., Barranco, M. J., Segura, R. J., & MartíNez, L. (2012). A mobile 3D-GIS hybrid recommender system for tourism. *Information sciences, 215*, 37-52.

Núñez-Valdéz, E. R., Lovelle, J. M. C., Martínez, O. S., García-Díaz, V., De Pablos, P. O., & Marín, C. E. M.

(2012). Implicit feedback techniques on recommender systems applied to electronic books. *Computers in Human Behavior, 28*(4), 1186-1193.

Pan, G., Qi, G., Zhang, W., Li, S., Wu, Z., & Yang, L. T. (2013). Trace analysis and mining for smart cities: issues, methods, and applications. *IEEE Communications Magazine, 51*(6), 120-126.

Park, D. H., Kim, H. K., Choi, I. Y., & Kim, J. K. (2012). A literature review and classification of recommender systems research. *Expert Systems with Applications, 39*(11), 10059-10072. doi:10.1016/j.eswa.2012.02.038

Payne, A., & Frow, P. (2005). A strategic framework for customer relationship management. *Journal of Marketing, 69*(4), 167-176.

Pereira, A. L. V., & Hruschka, E. R. (2015). Simultaneous co-clustering and learning to address the cold start problem in recommender systems. *Knowledge-Based Systems, 82*, 11-19.

Portugal, I., Alencar, P., & Cowan, D. (2018). The use of machine learning algorithms in recommender systems: A systematic review. *Expert Systems with Applications, 97*, 205-227.

Rickenberg, T. A., Neumann, M., Hohler, B., & Breitner, M. (2012). *Enterprise content management-A literature review.* Paper presented at the Proceedings of the Eighteenth Americas Conference on Information Systems.

Rygielski, C., Wang, J.-C., & Yen, D. C. (2002). Data mining techniques for customer relationship management. *Technology in society, 24*(4), 483-502.

Sanchez, F., Barrilero, M., Uribe, S., Alvarez, F., Tena, A., & Menendez, J. M. (2012). Social and content hybrid image recommender system for mobile social networks. *Mobile Networks and Applications, 17*(6), 782-795.

Sánchez-Moreno, D., González, A. B. G., Vicente, M. D. M., Batista, V. F. L., & García, M. N. M. (2016). A collaborative filtering method for music recommendation using playing coefficients for artists and users. *Expert Systems with Applications, 66*, 234-244.

Sassi, I. B., Mellouli, S., & Yahia, S. B. (2017). Context-aware recommender systems in mobile environment: On the road of future research. *Information Systems, 72*, 27-61.

Scellato, S., Noulas, A., & Mascolo, C. (2011). *Exploiting place features in link prediction on location-based social networks.* Paper presented at the Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining.

Schafer, J. B., Frankowski, D., Herlocker, J., & Sen, S. (2007). Collaborative filtering recommender systems. In B. Peter, K. Alfred, & N. Wolfgang (Eds.), *The adaptive web* (pp. 291-324): Springer-Verlag.

Sejal, D., Rashmi, V., Venugopal, K., Iyengar, S., & Patnaik, L. (2016). Image recommendation based on keyword relevance using absorbing Markov chain and image features. *International Journal of Multimedia Information Retrieval, 5*(3), 185-199.

Siu, N. Y.-M., Zhang, T. J.-F., Dong, P., & Kwan, H.-Y. (2013). New service bonds and customer value in customer relationship management: The case of museum visitors. *Tourism Management, 36*, 293-303.

Tkalcic, M., Odic, A., Kosir, A., & Tasic, J. (2012). Affective labeling in a content-based recommender system for images. *IEEE Transactions on Multimedia, 15*(2), 391-400.

Umanets, A., Ferreira, A., & Leite, N. (2014). GuideMe–A tourist guide with a recommender system and social interaction. *Procedia Technology, 17*, 407-414.

van Capelleveen, G., Amrit, C., Yazan, D. M., & Zijm, H. (2019). The recommender canvas: a model for developing and documenting recommender system design. *Expert Systems with Applications, 129*, 97-117.

Viktoratos, I., Tsadiras, A., & Bassiliades, N. (2018). Combining community-based knowledge with association rule mining to alleviate the cold start problem in context-aware recommender systems. *Expert Systems with Applications, 101*, 78-90.

Villegas, N. M., Sánchez, C., Díaz-Cely, J., & Tamura, G. (2018). Characterizing context-aware recommender systems: A systematic literature review. *Knowledge-Based Systems, 140*, 173-200.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*, xiii-xxiii.

Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing, 80*(6), 97-121. doi:10.1509/jm.15.0413

Yang, W.-S., & Hwang, S.-Y. (2013). iTravel: A recommender system in mobile peer-to-peer environment. *Journal of Systems Software, 86*(1), 12-20.

Yao, L., Sheng, Q. Z., Segev, A., & Yu, J. (2013). *Recommending web services via combining collaborative filtering with content-based features.* Paper presented at the 2013 IEEE 20th International Conference on Web Services.

Zhang, H.-R., & Min, F. (2016). Three-way recommender systems based on random forests. *Knowledge-Based Systems, 91*, 275-286.

Zhang, J., Yang, Y., Tian, Q., Zhuo, L., & Liu, X. (2017). Personalized social image recommendation method based on user-image-tag model. *IEEE Transactions on Multimedia, 19*(11), 2439-2449.

Zheng, E., Kondo, G. Y., Zilora, S., & Yu, Q. (2018). Tag-aware dynamic music recommendation. *Expert Systems with Applications, 106*, 244-251.

Zhou, M. (2010). *Book recommendation based on web social network.* Paper presented at the 2010 international conference on artificial intelligence and education (ICAIE).