Context-aware Knowledge-based Systems: A Literature Review

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Abstract

Context awareness systems, a subcategory of intelligent systems, are concerned with suggesting relevant products/services to users' situations as smart services. One key element for improving smart services' quality is to organize and manipulate contextual data in an appropriate manner to facilitate knowledge generation from these data. In this light, a knowledge-based approach, can be used as a key component in context-aware systems. Context awareness and knowledge-based systems, in fact, have been gaining prominence in their respective domains for decades. However, few studies have focused on how to reconcile the two fields to maximize the benefits of each field. For this reason, the objective of this paper is to present a literature review of how context-aware systems, with a focus on the knowledge-based approach, have recently been conceptualized to promote further research in this area. In the end, the implications and current challenges of the study will be discussed.

Keywords: Knowledge-based, Context-aware, Knowledge system, Literature review.

1. Introduction

Due to advancements in ubiquitous computing, along with the evolution of big data, the impact of context awareness has increased considerably across various fields such as computing, big data, IoT, or information systems (IS) (Pradeep & Krishnamoorthy, 2019). In the field of IS, context awareness is considered as a significant factor to improve users' services. The capacity of systems to provide services and/or products appropriate to the circumstance of users is essential to improve their satisfaction and their engagement. Those systems are termed as smart or context-aware systems (Dam et al., 2021, 2022; Le Dinh & Dam, 2021), which is considered as a subcategory of intelligent systems (Dreyer et al., 2021). With the proliferation of data in the digital area, context information can be acquired from various sources (sensors, web services, or other data repositories). Hence, context data can be enormous, highly heterogeneous, and complex to be processed. Leveraging context data to improve smart services, therefore, is a non-trivial task. To address this issue, contextual data should be well-organized and transformed to useful knowledge in smart systems, (Dreyer et al., 2021). From this perspective, knowledge-based approaches show their influence in context-aware systems due to their capability of representation and inference. The importance of context awareness and knowledge, especially in the IS domain, is highlighted in the literature (Beverungen et al., 2017; Dam et al., 2022; Dreyer et al., 2021; Le Dinh et al., 2021). The majority of context awareness research is concerned with the engineering aspect of processing raw contextual data from sensors and applying that processed data in smart environments (smart homes, smart cities, or devices). Knowledge-centric research, on the other hand, is concerned with the managerial or the business aspect of representing, manipulating, and disseminating knowledge to generate (business) insights (Alavi & Leidner, 2001). Few studies concentrate on how to reconcile the two fields to propose a holistic and comprehensive approach for the conception and application of context-aware capacities and knowledge bases in smart systems. Consequently, an examination of context-aware systems in conjunction with knowledge-centric research is required. These smart

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systems are known as context-aware knowledge-based systems (Le Dinh et al., 2021).

To stimulate future works on context-aware knowledge-based systems, this paper aims at providing an overall synthesis of how to conceptualize and implement context-aware systems, which leverage knowledge-based approaches to provide smart services to users. To achieve this objective, this paper addresses the following research questions: *What is the state of the art in the conception and development of a context-aware system, with an integration of knowledge bases?* More precisely, this paper focuses on behavioral (i.e., processes or steps/activities to design and implement a system) and structural aspects (i.e., components of a system), which must be considered in any system conception and design.

Accordingly, the remainder of this paper is structured as follows. Section 2 focuses on the theoretical background related to context awareness systems and the utilization of knowledge bases. Section 3 presents other literature related to context-aware systems and/or knowledge-based systems. Section 4 continues with the adopted methodology to conduct this literature review. To respond to the research questions identified, Section 5 describes the classification of selected studies regarding behavioral and structural aspects of a system conception and development. Section 6 presents analysis results. A brief discussion of research implications and future research directions is also described in Section 7. Finally, Section 8 provides a summary of findings.

2. Theoretical background

This section briefly presents the theoretical background on which this literature is conducted, including the notion of context-aware system and the role of knowledge bases in those systems.

Context is defined as any information that helps identify the situation of an entity (e.g., a specific user in smart services; Abowd et al., 1999). Context information, from the IS perspective, can describe user context (e.g., user profiles or preferences; Feng et al., 2004; Kang et al., 2008) or environmental context (e.g., time, location, or devices related to a particular user; Feng et al., 2004; Kang et al., 2008). Accordingly, context-aware systems (also termed as smart systems) are the ones, which have the capacity for acquisition, processing, and utilization of context information to provide services relevant to users' situations (Sánchez-Pi et al., 2012). To facilitate the conception of context-aware systems, various studies have been proposed to clarify the main stages of the transformation from context information to deliverable services (Bernardos et al., 2008; Hu et al., 2008; Perera et al., 2014; Pradeep & Krishnamoorthy, 2019).

The knowledge-based approach is a research domain, which has reached the maturity for decades. A knowledge-based system is defined as a system that reasons and uses a knowledge base to solve complex problems. From context-aware system practices, a knowledge base supports the process of structuring tasks, inference rules, domain knowledge, or context information into a suitable form to enhance the reasoning process (Sánchez-Pi et al., 2012). A knowledge-based approach, which places emphasis on how to structure data in a meaningful way, aims at increasing the accuracy and efficiency of context awareness (Al Nuaimi et al., 2015).

3. Related work

This part analyzes other literature reviews, which have been conducted on the conception and development of context-aware systems and/or knowledge-based systems to explain the motivations underlying this study. These issues have been studied in the literature for decades.

In the context-aware research stream, various studies have been published to clarify concepts related to context-aware systems, as well as processes/methods for conceptualizing and implementing those systems. For example, Perera et al. (2014) introduce a general framework, which captures various aspects such as techniques for context acquisition and reasoning, models, or main components of context-aware ecosystems from an IoT perspective. Bibri and Krogstie (2017), and Dinh et al. (2020) examine the application of context awareness through the lens of big data analytics. Abbas et al. (2015) concentrate on key characteristics of context-aware recommendation systems built upon AI-based techniques such as fuzzy logic, and Artificial Neuron Networks (see also Champiri et al., 2015; Villegas et al., 2018). Pradeep and Krishnamoorthy (2019) highlight three building components (Modeling, Organisation, and Middleware) to develop context-aware systems.

In the knowledge-centric research stream, knowledge has an inevitable role to provide context-aware services/products efficiently (Al Nuaimi et al., 2015; see also Dreyer et al., 2021; Le Dinh et al., 2021). However, Dreyer et al. (2021) aim at clarifying requirements and design principles for knowledge management systems for smart services rather than examining all phases from design to implementation of those systems. Le Dinh et al. (2021), on the other hand, emphasize different knowledge components (e.g., know-who, know-what) used in context-aware systems but do not mention technical aspects for implementation (e.g., algorithms used for context reasoning, models employed for context modeling).

A number of studies on context-aware system conception and design could be found in the literature. However, to the best of our knowledge, there are few studies focusing on the connection between knowledge management and context-aware systems.

4. Methodology

To conduct this literature review, a search design based upon a concept-centric methodology was adopted (Webster & Watson, 2002). Figure 1 depicts the search process carried out to complete this literature, including five stages: Identification, Abstract screening, Full text scanning, Backward and forward searches, and Selection.

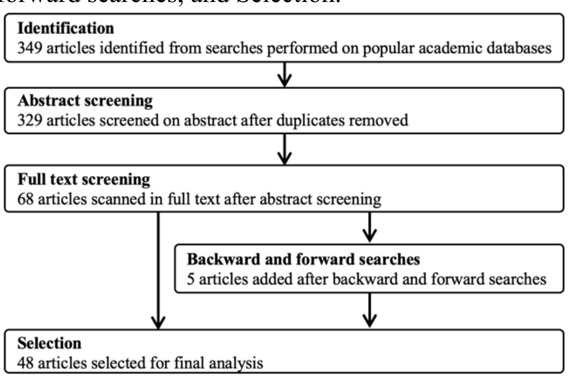

Figure 1. Search process

In **Identification** stage, searches were performed on popular academic databases, including ProQuest, ScienceDirect, JSTOR, IEEE Xplore, and ACM Digital Library. The relevant articles were retrieved by using two key indicators: "context-aware" (or its synonym: "context awareness") and "knowledge" on articles' title, abstract, or keywords. This paper only takes into account articles published between 2014-2022 in peer-reviewed conferences and/or leading journals in information systems with a high impact factor to ensure a comprehensive and high-quality review.

In **Abstract screening** stage, articles met one of the following exclusion criteria (EC) will be eliminated. EC#1: Articles focus on NLP processing or AI algorithms rather than on an overall approach for conception and development of smart systems. EC#2: The notion "knowledge" is not mentioned.

In **Full text scanning** stage, articles met all following inclusion criteria (IC) will be chosen. IC#1: Components and processes for constructing a context-aware system are clarified and considered as major contributions. IC#2: Knowledge bases are mentioned as an important part in the context-aware systems.

Backward and forward searches were also conducted to guarantee the selection of the most relevant publications (Webster & Watson, 2002).

Finally, in **Selection** stage, 48 articles are chosen for final analysis.

Table 1 presents the distribution of selected papers. According to Table 1, the significant proportion of relevant articles comes from Expert Systems with Applications (33%), followed by Knowledge-Based System (23%), and other Q1 journals (the top 25% of journals, according to Scimago ranking) in the information system or pervasive computing (26%). Other conference papers, which are also well-referenced, are the proceedings retrieved from ACM, AIS, and IEEE.

Table 1. Distribution of selected papers

Journal	Quantity	Percentage
Expert Systems with Applications	17	33%
Knowledge-Based Systems	11	23%
Pervasive Computing	4	8%
Decision Support Systems	3	6%
Computers in Industry	3	6%
Engineering Applications of Artificial Intelligence	2	4%
Information & Management	1	2%
Other conference papers retrieved from IEEE, ACM, AIS	7	13%
Total	48	100%

5. Classification of selected papers

This section introduces key factors for grouping the retrieved articles, which cover two aspects of a context-aware knowledge-based system: behavioral and structural aspects.

The behavioral aspect deals with processes/methods and techniques of transformation from contextual data to deliverable services. Inspired by the proposition of Perera et al (2014), Pradeep and Krishnamoorthy (2019), and Sánchez-Pi et al. (2012), the behavioral aspect is concerned with four factors as follows. **Acquisition** gathers context information from diverse sources. **Representation** organizes context information in a suitable structure, according to the purpose and application. **Reasoning** exploits context information to derive meaningful knowledge. **Dissemination** deals with how to deliver context-based services to users (Perera et al., 2014).

The structural aspect provides an overview of the storage components of a context-aware knowledge-based system. This aspect consists of three factors as follows. **Data repositories** and **knowledge bases** act as storage units. Data repositories are usually based upon a tabular structure, whereas knowledge bases require a **knowledge structure** (or knowledge model) (Le Dinh & Dam, 2021) to represent entities within a knowledge base and their relationships.

Each factor is considered as a unit of analysis (Webster & Watson, 2002). Table 2 describes a synthesis of selected articles according to the 7-units of analysis. The articles are noted with three degrees of intensity: highly cover (***), moderately cover (**), and slightly cover (*) (Dam & Dinh, 2020; Rickenberg et al., 2012).

Table 2. Synthesis of selected articles

	Behavioral aspect				Structural aspect		
Article	**Acquisition**	**Representation**	**Reasoning**	**Dissemination**	**Data repository**	**Knowledge structure**	**Knowledge base**
Livne et al. (2022)	***						
Del Carmen Rodríguez-Hernández and Ilarri (2021)	*		*	**		*	
Hussain et al. (2021)	*		*		*		*
Li et al. (2021)	**	**	**		*		*
Musto et al. (2021)		***	***				
Yuen et al. (2021)			***				
Campana and Delmastro (2021)	***						
Oh et al. (2021)	***						
Huet et al. (2021)	*	***	***			*	*
Fertier et al. (2021)	*	**	*	*	*	*	*
Iqbal et al. (2021)		***	**			*	*
Alsaig et al. (2020)		***	***	*		*	
Bettini et al. (2020)		**	**	*	*	**	**
Liu et al. (2020)			***				
E. J. Kim et al. (2019)				***			
Song et al. (2019)	***	**	***	**			*
J. Kim et al. (2019)	***	*	***	**	*	*	*
Afzal et al. (2018)	*	*	**	***	*	*	*
Nogueira et al. (2018)	*	***	*	*	*	**	*
Navarro et al. (2018)	**	***	**	**		**	*
Obaidat et al. (2018)	***	**	**	*		*	*
Esposito et al. (2018)	***	***	***		**	**	**
Haque and Khan (2018)		**	***			**	**
Minkov et al. (2017)		*	***				
Chahuara et al. (2017)	***	**	***			**	*
Xiao et al. (2017)	***	***			*		*
Garcia-de-Prado et al. (2017)	***		**				
Pramanik et al. (2017)	*	*	*	*	*		*
Mishra et al. (2017)	*	***	***	**		**	*
Meditskos and Kompatsiaris (2017)		**	**				
Unger et al. (2016)	***		***			*	
Sundermann et al. (2016)	**		**		*		

Article	Behavioral aspect				Structural aspect		
	Acquisition	Representation	Reasoning	Dissemination	Data repository	Knowledge structure	Knowledge base
Barbosa et al. (2016)		*		***	*	*	
Zhu et al. (2016)		***	**				
Bradesko et al. (2016)	*	***	***			**	***
Meditskos et al. (2016)	*	**	***			**	**
Hou et al. (2015)	***	***	***		*	*	*
Aihe and Gonzalez (2015)	***	**					
Colombo-Mendoza et al. (2015)	*	*	***	*			
Muñoz et al. (2015)		***	**				
Viktoratos et al. (2018)	*	**	***	**		*	*
Lee et al. (2015)	***						
Sohn et al. (2015)	**		**	*			
Evchina et al. (2015)	**	***	***		*	*	*
Díaz Rodríguez et al. (2014)		***	***			***	*
Neves et al. (2014)		**	**	*			
Nguyen et al. (2014)	**	***	***	**		***	*
Han et al. (2014)		***	***				
Total (articles)	32	35	40	19	14	24	25
Total (weighted)	66	81	97	32	15	37	31
Notation: highly cover (*x1), moderately cover (**x2), and slightly cover (***x3)							

6. Analysis of the literature review

This section presents analysis results of selected papers according to 7 units of analysis as mentioned before. The detailed analysis is presented as follows.

6.1. Behavioral aspect

As presented in Table 2, four factors of the behavioral aspect, except the Dissemination factor, have attracted significant research attention, with 67%, 73%, and 83% of reviewed papers considering the perspectives of acquisition, representation, and reasoning in their studies, respectively. The following is a **summary** of current research on these factors.

Acquisition. 32 articles involve context acquisition, which is responsible for collecting and extracting contextual information from physical sources (sensors) or virtual sources (websites or data repositories). Context information can be classified as low-level and high-level context (Afzal et al., 2018; Perera et al., 2014). *Low-level context* is retrieved directly from physical sensors and is mainly less meaningful. *High-level context*, which is more meaningful and suitable for reasoning, can be extracted from low-level data through advanced processing techniques (Perera et al., 2014). Machine learning techniques were adopted to discover hidden contexts from raw data (Livne et al., 2022; Unger et al., 2016). For example, Campana and Delmastro (2021) apply clustering algorithms to extract environmental context (e.g., location, nearby devices) from the mobiles. Afzal et al. (2018), Chahuara et al. (2017), and E. J. Kim et al. (2019) emphasize the separation between a low-level and high-level context for accurate reasoning and the capacity of reusability.

Representation. A total of 35 articles deals with context modeling/representation, which focus on organizing context data in an appropriate format for reasoning. Among many context modeling techniques (e.g., markup schema, object-based, logic-based), the *ontology-based approach* is still the most prominent tool due to its expressiveness and rich capacity of reasoning (Perera et al., 2014). In most reviewed articles, ontologies are adopted to model context, content domain, activities/tasks, and many others (Bettini et al., 2020; Chahuara et al., 2017; Colombo-Mendoza et al., 2015; Díaz Rodríguez et al., 2014; Muñoz et al., 2015; Neves et al., 2014). Besides, the *logic-based approach* can help represent contextual knowledge through declarative languages (Alsaig et al., 2020; Xiao et al., 2017). Literature also acknowledges the use of *knowledge graphs* (Hogan et al., 2021) in organizing more complex context data (e.g., social interaction context; Hou et al., 2015; Huet et al., 2021; Musto et al., 2021).

Reasoning. Context reasoning involves knowledge generation by inferring context data (Perera et al., 2014). As presented in Table 2, context reasoning, along with context representation, has gained great attention from research communities. 40 articles emphasize their focus on context reasoning. Various reasoning techniques (e.g., supervised, unsupervised, logic-based, ontology/semantic-based, fuzzy-based, rule-based) can be applied to exploit context data. Adoption of these techniques must conform with selected modeling techniques (Perera et al., 2014). Due to the dominance of ontology-based modeling, *semantic-based* (Díaz Rodríguez et al., 2014; Muñoz et al., 2015; R. Song et al., 2019) and *rule-based* (Huet et al., 2021; Viktoratos et al., 2018) techniques are adopted in numerous studies. *Graph-based reasoning*, where the reasoning is performed on edges of graphs through graph-based algorithms (e.g., random walk), can also be adopted for context extraction and mapping (Han et al., 2014). Finally, a *hybrid approach* combining different reasoning techniques is proposed to overcome the drawbacks of each technique (Alsaig et al., 2020; Bettini et al., 2020; Díaz Rodríguez et al., 2014; Perera et al., 2014).

Dissemination. Stemming from the definition in (Perera et al., 2014), this study extends and defines dissemination as means used to deliver context-based services to users. Only 19 articles mention service delivery as a part of their system. Context-based services can be *employed in specific applications* (recommendation systems, or healthcare monitoring systems) and *delivered through interfaces* (Colombo-Mendoza et al., 2015; Sohn et al., 2015). Some articles, particularly, highlight the dissemination by explicitly determining an *application layer of delivery services* (Afzal et al., 2018; Navarro et al., 2018).

Based on current research on four factors of the behavioral aspect presented above, the following **research gaps** have been identified.

G#1. Acquiring high-level context appears to draw less attention. User profiles or preferences, which are critical to personalized services, have received little attention in context-aware systems.

G#2. Context data can come from a variety of large-scale and heterogeneous sources (Pauleen & Wang, 2017). The issues of adapting context modelling to such complex data have not been studied.

G#3. From knowledge-centric research, context reasoning factor is less discussed.

G#4. Service dissemination/delivery does not seem to have attracted much attention.

6.2. Structural aspect

In terms of the structural aspect, the weight demonstrates that storage dimension is not highlighted in the selected articles; however, they are still the major components in context-aware systems. A **summary** of current research on these factors is provided below.

Data repository. In knowledge-based systems, data repositories (i.e., enterprise data storage entities into which data has been specifically partitioned for an analytical or reporting purpose) are often used to store *low-level data*, which are primarily retrieved from sensors. Only 14 articles concern data repository. Data repositories can store low-level context data for further processing (E. J. Kim et al., 2019; Sundermann et al., 2016; Xiao et al., 2017), or even *high-level context* data such as user profiles (Colombo-Mendoza et al., 2015; Li et al., 2021).

Knowledge base. Knowledge bases are generally utilized to store more meaningful information, which are usually derived from low-level data through mining techniques. 25 articles mention knowledge base in their studies. While data repositories contain mainly low-level data, knowledge bases are generally utilized to store more meaningful data. In context-aware systems, knowledge bases are responsible for containing *high-level context* (Bettini et al., 2020; Chahuara et al., 2017; Navarro et al., 2018), *content domain* (Díaz Rodríguez et al., 2014; Navarro et al., 2018; Neves et al., 2014), *rules* for context reasoning (Hussain et al., 2021; Viktoratos et al., 2018; Xiao et al., 2017), and many others (Bettini et al., 2020; Chahuara et al., 2017). Ontologies are still the most popular means for knowledge bases.

Knowledge structure. A knowledge structure defines concepts and/or interrelations between the concepts, which are used for organizing information in the knowledge base. From the IS perspective, a knowledge model can feature various knowledge components, for example, know-who, know-what, know-how, know-when, know-who (Le Dinh et al., 2021). To facilitate the reasoning process and improve reasoning accuracy, high-level context data and other information related to reasoning (e.g., content data) need to be organized in a suitable structure (i.e., knowledge structure or model; Alsaig et al., 2020; Xiao et al., 2017). This structure defines relationships and constraints between context information. 24 articles mention knowledge structure (or knowledge model) in their studies (Alsaig et al., 2020; Esposito et al., 2018; Haque & Khan, 2018; Navarro et al., 2018; Nogueira et al., 2018).

The preceding synthesis has revealed the following **research gap** on context-aware knowledge base's structural aspect.

G#5. According to the research gaps G#2 and #3, knowledge bases and structures should consider large-scale and heterogeneous sources to propose effective context-aware services. However, the issues of how to construct knowledge bases based upon an appropriate structure to generate insights for smart services have not been mentioned in current research.

7. Discussion and future research directions

This section discusses future research directions related to the conception and design of context-aware knowledge-based systems to address the identified research gaps. These trends are summarized in Table 3 and discussed further in the following sections.

Table 3. Summary of future trends

Future trends	Research gaps
High-level context acquisition	*G#1*
Reasoning from the business perspective	*G#3*
Service dissemination solutions	*G#4*
Knowledge bases for context-aware systems	*G#2, G#5*
Towards a combined solution	G#1→G#5

High-level context acquisition. Extracting data from sensors has been researched for a long time in the field of ubiquitous computing or the internet of things. In these domains, researchers mostly focus on the extraction of low-level context data from sensors through data mining or machine learning techniques. The low-level, however, are not suitable for reasoning processes (Alsaig et al., 2020) and even meaningless in terms of business goals (R. Song et al., 2019). Indeed, exploring high-level context (e.g., user preferences or profiles) plays a significant role to produce more valuable business insights. Deducing high-level context from low-level data is a non-trivial task due to the complexity of raw data. Further studies on the acquisition of high-level context such as user profiles or preferences are important for a more efficient context-aware system.

Reasoning from the business perspective. Many papers emphasizing context reasoning demonstrate its significance. However, the question of how to select and/or implement context reasoning techniques appropriate for more meaningful knowledge generation from diverse context data is still a challenging task. Many techniques born in the AI field (e.g., supervised/unsupervised learning, Artificial Neuron Networks) may be effective in processing raw data to acquire context information (Perera et al., 2014), but they may not be dedicated to inferring context from the managerial and business perspectives. This inference may help to response to business questions such as what services/products should be delivered to whom, for what reasons, and how should those services be used?

Service dissemination solutions. In a society dominated by services, data are valuable only if they can be transferred to knowledge, which in turn are applied to generate insights (Dam et al., 2022; Malik et al., 2019). From this perspective, context needs to be delivered to create value. Only knowledge application can lead to enhance organization performance (Alavi & Leidner, 2001). Even though several studies or other literature reviews have mentioned delivery models for context-based services (Colombo-Mendoza et al., 2015; Navarro et al., 2018), not enough attention has been given to this factor.

Knowledge bases for context-aware systems. Knowledge have a significant impact on the provision of high-quality context-aware services (Al Nuaimi et al., 2015). With the rapid expansion of data due to the evolution of technologies, it is critical to structure knowledge in a way that facilitates various sources of data (Pauleen & Wang, 2017). As revealed in the literature, context should be well structured in knowledge bases to facilitate the reasoning process. Context modeling/representation must be also suitable to such complex knowledge. Knowledge graphs and ontologies may be promising solutions for representing large and complex context data (Hogan et al., 2021). However, structuring and implementing of knowledge bases dedicated to context-aware systems should be further investigated.

Towards a combined solution. According to the analysis of selected papers, context-aware and knowledge-centric research remain important topics and trends in their respective domains. Each research stream, however, has a distinct focus. In context-aware stream, researchers concentrate on context data acquisition and reasoning rather than knowledge application for business insight generation. In knowledge management stream, various approaches have been proposed to organize and disseminate knowledge to generate insights within an organization, but there has been less emphasis on the contextual factor of knowledge-based systems (Hussain et al., 2021). To facilitate the conception and design of context-aware knowledge-based systems, a combined solution, which considers both knowledge management and context-aware design aspects, needs to be further investigated.

8. Conclusion

Nowadays, smart systems play an important role to improve users' satisfaction and engagement. In those systems, context awareness is considered a vital factor to enable the intelligence of those systems. The topic of context awareness, which originated in the pervasive computing domain, has been investigated for decades. However, numerous studies concentrate on applying techniques to acquire context information from raw data rather than organizing context data in a way that can facilitate insight generation. In order to promote the design of context-aware systems with the focus on the inside generation, the paper presents a holistic overview of how those systems have been studied in the current literature review.

In terms of originality and findings, this is the first paper to examine smart systems through two lenses: computing and IoT, which covers context awareness; and knowledge management, which covers knowledge representation, manipulation, and application for insight generation. The findings of the paper can help to clarify the overall process of transforming contextual data to insights through various stages (Acquisition, Representation, Reasoning, and Dissemination). These findings also shed light on the significance of a knowledge model and knowledge bases within a smart system. This type of synthesis can, first and foremost, enrich the literature. Secondly, it can help to advance future research directions from two perspectives: computing and knowledge-centric research streams.

9. References

Abbas, A., Zhang, L., & Khan, S. U. (2015). A survey on context-aware recommender systems based on computational intelligence techniques. *Computing*, *97*(7), 667–690.

Abowd, G. D., Dey, A. K., Brown, P. J., Davies, N., Smith, M., & Steggles, P. (1999). Towards a Better Understanding of Context and Context-Awareness. *Handheld and Ubiquitous Computing*, 1707, pp. 304–307.

Afzal, M., Ali, S. I., Ali, R., Hussain, M., Ali, T., Khan, W. A., Amin, M. B., Kang, B. H., & Lee, S. (2018). Personalization of wellness recommendations using contextual interpretation. *Expert Systems with Applications*, *96*, 506–521.

Aihe, D. O., & Gonzalez, A. J. (2015). Correcting flawed expert knowledge through reinforcement learning. *Expert Systems with Applications*, *42*(17–18).

Al Nuaimi, E., Al Neyadi, H., Mohamed, N., & Al-Jaroodi, J. (2015). Applications of big data to smart cities. *Journal of Internet Services and Applications*.

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Quarterly*, *25*(1), 107–136.

Alsaig, A., Alagar, V., & Nematollaah, S. (2020). Contelog: A declarative language for modeling and reasoning with contextual knowledge. *Knowledge-Based Systems*, *207*, 106403.

Barbosa, J. L. V., Martins, C., Franco, L. K., & Barbosa, D. N. F. (2016). TrailTrade: A model for trail-aware commerce support. *Computers in Industry*, *80*.

Bernardos, A. M., Tarrio, P., & Casar, J. R. (2008). A data fusion framework for context-aware mobile services. *2008 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 606–613.

Bettini, C., Civitarese, G., & Presotto, R. (2020). CAVIAR: Context-driven Active and Incremental Activity Recognition. *Knowledge-Based Systems*, *196*.

Beverungen, D., Matzner, M., & Janiesch, C. (2017). Information systems for smart services. *Information Systems and E-Business Management*, *15*(4), 781–787.

Bibri, S. E., & Krogstie, J. (2017). The core enabling technologies of big data analytics and context-aware computing for smart sustainable cities: A review and synthesis. *Journal of Big Data*, *4*(1).

Bradesko, L., Starc, J., Mladenic, D., Grobelnik, M., & Witbrock, M. (2016). Curious cat conversational crowd based and context aware knowledge acquisition chat bot. *2016 IEEE 8th International Conference on Intelligent Systems (IS)*, 239–252.

Campana, M. G., & Delmastro, F. (2021). COMPASS: Unsupervised and online clustering of complex human activities from smartphone sensors. *Expert Systems with Applications*, *181*, 115124.

Chahuara, P., Portet, F., & Vacher, M. (2017). Context-aware decision making under uncertainty for voice-based control of smart home. *Expert Systems with Applications*, *75*, 63–79.

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.

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.

Dam, N., & Dinh, T. (2020). A Literature Review of Recommender Systems for the Cultural Sector: *Proceedings of the 22nd International Conference on Enterprise Information Systems*, 715–726.

Dam, N., Le Dinh, T., & Menvielle, W. (2021). Towards a Conceptual Framework for Customer Intelligence in the Era of Big Data. *International Journal of Intelligent Information Technologies*, *17*.

Dam, N., Le Dinh, T., & Menvielle, W. (2022). The Quest for Customer Intelligence to Support Marketing Decisions: A Knowledge-Based Framework. *Vietnam Journal of Computer Science,* 9(3).

Del Carmen Rodríguez-Hernández, M., & Ilarri, S. (2021). AI-based mobile context-aware recommender systems from an information management perspective: Progress and directions. *Knowledge-Based Systems*, *215*, 106740.

Díaz Rodríguez, N., Cuéllar, M. P., Lilius, J., & Delgado Calvo-Flores, M. (2014). A fuzzy ontology for semantic modelling and recognition of human behaviour. *Knowledge-Based Systems*, *66*, 46–60.

Dinh, L. T. N., Karmakar, G., & Kamruzzaman, J. (2020). A survey on context awareness in big data analytics for business applications. *Knowledge and Information Systems*, *62*(9), 3387–3415.

Dreyer, S., Werth, O., Olivotti, D., Guhr, N., & Breitner, M. H. (2021). *Knowledge Management Systems for Smart Services: A Synthesis of Design Principles*.

Esposito, M., Minutolo, A., Megna, R., Forastiere, M., Magliulo, M., & De Pietro, G. (2018). A smart mobile, self-configuring, context-aware architecture for personal health monitoring. *Engineering Applications of Artificial Intelligence*, *67*, 136–156.

Evchina, Y., Puttonen, J., Dvoryanchikova, A., & Lastra, J. L. M. (2015). Context-aware knowledge-based middleware for selective information delivery in data-intensive monitoring systems. *Engineering Applications of Artificial Intelligence*, *43*.

Feng, L., Apers, P. M. G., & Jonker, W. (2004). Towards Context-Aware Data Management for Ambient Intelligence. *In Proc. of the 15th Intl. Conf. on Database and Expert Systems Applications*.

Fertier, A., Martin, G., Barthe-Delanoë, A.-M., Lesbegueries, J., Montarnal, A., Truptil, S., Bénaben, F., & Salatgé, N. (2021). Managing events to improve situation awareness and resilience in a supply chain. *Computers in Industry*, *132*, 103488.

Garcia-de-Prado, A., Ortiz, G., & Boubeta-Puig, J. (2017). COLLECT: COLLaborativE ConText-aware service oriented architecture for intelligent decision-making in the Internet of Things. *Expert Systems with Applications*, *85*, 231–248.

Han, J., Schmidtke, H. R., Xie, X., & Woo, W. (2014). Adaptive content recommendation for mobile users: Ordering recommendations using a hierarchical context model with granularity. *Pervasive and Mobile Computing*, *13*, 85–98.

Haque, H. M. U., & Khan, S. U. (2018). A context-aware reasoning framework for heterogeneous systems. *2018 International Conference on Advancements in Computational Sciences (ICACS)*, 1–9.

Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., de Melo, G., Gutierrez, C., Gayo, J. E. L., Kirrane, S., Neumaier, S., Polleres, A., Navigli, R., Ngomo, A.-C. N., Rashid, S. M., Rula, A., Schmelzeisen, L., Sequeda, J., Staab, S., & Zimmermann, A. (2021). Knowledge Graphs. *ACM Computing Surveys*, *54*(4), 1–37.

Hou, L., Li, J., Wang, Z., Tang, J., Zhang, P., Yang, R., & Zheng, Q. (2015). NewsMiner: Multifaceted news analysis for event search. *Knowledge-Based Systems*, *76*, 17–29.

Hu, P., Indulska, J., & Robinson, R. (2008). An Autonomic Context Management System for Pervasive Computing. *2008 Sixth Annual IEEE International Conference on Pervasive Computing and Communications (PerCom)*.

Huet, A., Pinquié, R., Véron, P., Mallet, A., & Segonds, F. (2021). CACDA: A knowledge graph for a context-aware cognitive design assistant. *Computers in Industry*, *125*, 103377.

Hussain, M., Satti, F. A., Ali, S. I., Hussain, J., Ali, T., Kim, H.-S., Yoon, K.-H., Chung, T., & Lee, S. (2021). Intelligent knowledge consolidation: From data to wisdom. *Knowledge-Based Systems*, *234*, 107578.

Iqbal, M. W., Ch, N. A., Shahzad, S. K., Naqvi, M. R., Khan, B. A., & Ali, Z. (2021). User Context Ontology for Adaptive Mobile-Phone Interfaces. *IEEE Access*, *9*, 96751–96762.

Kang, H., Suh, E., & Yoo, K. (2008). Packet-based context aware system to determine information system user's context. *Expert Systems with Applications*, *35*(1–2), 286–300.

Kim, E. J., Jun, J. A., Kim, N.-S., & Pyo, C. S. (2019). The method for hierarchical context awareness based on activity recognition. *2019 International Conference on Information and Communication Technology Convergence (ICTC)*, 974–976.

Kim, J., Chang, Y., Chong, A. Y. L., & Park, M.-C. (2019). Do perceived use contexts influence usage behavior? An instrument development of perceived use context. *Information & Management*, *56*(7), 103155.

Le Dinh, T., & Dam, N. A. K. (2021). Towards Smart Customer Knowledge Management Systems. In K. Wojtkiewicz, J. Treur, E. Pimenidis, & M. Maleszka (Eds.), *Advances in Computational Collective Intelligence,* 1463, 225–238.

Le Dinh, T., Pham Thi, T. T., Pham-Nguyen, C., & Nam, L. N. H. (2021). A knowledge-based model for context-aware smart service systems. *Journal of Information and Telecommunication*, 1–22.

Lee, S.-H., Yang, K.-M., & Cho, S.-B. (2015). Integrated modular Bayesian networks with selective inference for context-aware decision making. *Neurocomputing*, *163*, 38–46.

Li, X., Chen, C.-H., Zheng, P., Jiang, Z., & Wang, L. (2021). A context-aware diversity-oriented knowledge recommendation approach for smart engineering solution design. *Knowledge-Based Systems*, *215*.

Liu, X., Zhang, J., & Yan, C. (2020). Towards context-aware collaborative filtering by learning context-aware latent representations. *Knowledge-Based Systems*.

Livne, A., Tov, E. S., Solomon, A., Elyasaf, A., Shapira, B., & Rokach, L. (2022). Evolving context-aware recommender systems with users in mind. *Expert Systems with Applications*, *189*, 116042.

Meditskos, G., Dasiopoulou, S., & Kompatsiaris, I. (2016). MetaQ: A knowledge-driven framework for context-aware activity recognition combining SPARQL and OWL 2 activity patterns. *Pervasive and Mobile Computing*, *25*, 104–124.

Meditskos, G., & Kompatsiaris, I. (2017). iKnow: Ontology-driven situational awareness for the recognition of activities of daily living. *Pervasive and Mobile Computing*, *40*, 17–41.

Minkov, E., Kahanov, K., & Kuflik, T. (2017). Graph-based recommendation integrating rating history and domain knowledge: Application to on-site guidance of museum visitors. *Journal of the Association for Information Science and Technology*, *68*(8), 1911–1924.

Mishra, M., Sidoti, D., Avvari, G. V., Mannaru, P., Ayala, D. F. M., Pattipati, K. R., & Kleinman, D. L. (2017). A Context-Driven Framework for Proactive Decision Support With Applications. *IEEE Access*, *5*, 12475–12495.

Muñoz, A., Lasheras, J., Capel, A., Cantabella, M., & Caballero, A. (2015). OntoSakai: On the optimization of a Learning Management System using semantics and user profiling. *Expert Systems with Applications*, *42*(15–16), 5995–6007.

Musto, C., Lops, P., de Gemmis, M., & Semeraro, G. (2021). Context-aware graph-based recommendations exploiting Personalized PageRank. *Knowledge-Based Systems*, *216*, 106806.

Navarro, N. de A. B., da Costa, C. A., Barbosa, J. L. V., & Righi, R. da R. (2018). Spontaneous Social Network: Toward dynamic virtual communities based on context-aware computing. *Expert Systems with Applications*, *95*, 72–87.

Neves, A. R. de M., Carvalho, Á. M. G., & Ralha, C. G. (2014). Agent-based architecture for context-aware and personalized event recommendation. *Expert Systems with Applications*, *41*(2), 563–573.

Nguyen, T., Loke, S. W., Torabi, T., & Lu, H. (2014). On the practicalities of place-based virtual communities: Ontology-based querying, application architecture, and performance. *Expert Systems with Applications*, *41*(6), 2859–2873.

Nogueira, T. P., Braga, R. B., de Oliveira, C. T., & Martin, H. (2018). FrameSTEP: A framework for annotating semantic trajectories based on episodes. *Expert Systems with Applications*, *92*.

Obaidat, M. S., Reddy, N. V. R., Venkata, K. P., & Saritha, V. (2018). Context-Aware Middleware Architectural Framework for Intelligent Smart Grid Data Management. *2018 International Conference on Computer, Information and Telecommunication Systems (CITS)*, 1–5.

Oh, B., Hwang, J., Seo, S., Chun, S., & Lee, K.-H. (2021). Inductive Gaussian representation of user-specific information for personalized stress-level prediction. *Expert Systems with Applications*, *178*.

Pauleen, D. J., & Wang, W. Y. C. (2017). Does big data mean big knowledge? KM perspectives on big data and analytics. *Journal of Knowledge Management*, *21*(1), 1–6.

Perera, C., Zaslavsky, A., Christen, P., & Georgakopoulos, D. (2014). Context Aware Computing for The Internet of Things: A Survey. *IEEE Communications Surveys & Tutorials*, *16*(1).

Pradeep, P., & Krishnamoorthy, S. (2019). The MOM of context-aware systems: A survey. *Computer Communications*, *137*, 44–69.

Pramanik, M. I., Lau, R. Y. K., Demirkan, H., & Azad, Md. A. K. (2017). Smart health: Big data enabled health paradigm within smart cities. *Expert Systems with Applications*, *87*, 370–383.

Rickenberg, T. A., Neumann, M., Hohler, B., & Breitner, M. (2012). Enterprise Content Management—A Literature Review. *AMCIS*.

Sánchez-Pi, N., Carbó, J., & Molina, J. M. (2012). A knowledge-based system approach for a context-aware system. *Knowledge-Based Systems*, *27*.

Sohn, M., Jeong, S., Kim, J., & Lee, H. J. (2015). Augmented context-based recommendation service framework using knowledge over the Linked Open Data cloud. *Pervasive and Mobile Computing*, *24*, 166–178.

Song, R., Vanthienen, J., Cui, W., Wang, Y., & Huang, L. (2019). Context-Aware BPM Using IoT-Integrated Context Ontologies and IoT-Enhanced Decision Models. *2019 IEEE 21st Conference on Business Informatics (CBI)*, 541–550.

Sundermann, C. V., Domingues, M. A., Conrado, M. da S., & Rezende, S. O. (2016). Privileged contextual information for context-aware recommender systems. *Expert Systems with Applications*, *57*.

Unger, M., Bar, A., Shapira, B., & Rokach, L. (2016). Towards latent context-aware recommendation systems. *Knowledge-Based Systems*, *104*.

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*, *26*(2), xiii–xxiii.

Xiao, X., Attanasio, A., Chiusano, S., & Cerquitelli, T. (2017). Twitter data laid almost bare: An insightful exploratory analyser. *Expert Systems with Applications*, *90*, 501–517.

Yuen, M.-C., King, I., & Leung, K.-S. (2021). Temporal context-aware task recommendation in crowdsourcing systems. *Knowledge-Based Systems*, *219*, 106770.

Zhu, X., vanden Broucke, S., Zhu, G., Vanthienen, J., & Baesens, B. (2016). Enabling flexible location-aware business process modeling and execution. *Decision Support Systems*, *83*, 1–9.