

*Review Article*

## **An Era of Recommendation Technologies in IoT: Categorisation by techniques, Challenges and Future Scope**

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### **ABSTRACT**

The evolution of the Internet of Things (IoT) accelerates the augmentation of data present on the Internet and possibilities for connections to the more dynamic and heterogeneous devices to the Internet. Recommendation technologies have proven their capabilities of digging the personalised information by proactive filtering in many application domains and can also be a backbone platform in IoT for identifying personalised things, services and relevant artefacts by prevailing over information overload problems. This paper is a comprehensive literature review that categorises IoT recommender systems by exploring the literature's different IoT based recommendation techniques. We conclude the paper by discussing the challenges and future scope for IoT based recommendations techniques to advancing and widening the frontiers of this research area.

*Keywords:* Context-awareness, IoT, knowledge-base, machine learning, recommender system, social IoT

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### **INTRODUCTION**

#### **Internet of Things**

The Internet of Things (IoT) is an integrated network of devices, things, physical objects with many embedded technologies. It is the junction of Internet-oriented vision, things oriented vision and semantics oriented vision (Čolaković & Hadžialić, 2018). IoT gives the addressable contribution in many applications and services like smart cities, smart homes, health monitoring,

wildlife monitoring, e-commerce, transport observations, building and home automation, manufacturing, agriculture, metropolitan scale development, energy management, environment monitoring, and medical enhancements. In the future, IoT will be responsible for hybridised the networks with its non-deterministic and dynamic nature that leads to the connection with billions of devices in a wide area of applications (Cha et al., 2017). Moreover, with the evolution of auto-organisation, self-learning, intelligent entities and virtual objects, IoT will act independently depending on the environment, context information and current circumstances.

### **Recommender Systems**

Recommender System (RS) is the information filtering tool from collected data. The systems offers users and service providers the advantage of filtering the information from the dynamic, flexible, huge volume, rich and diverse data sources according to the users' observed behaviour, preferences and interest. There are many application domains where RS are implemented, like e-commerce, e-libraries, e-business services, e-learning, cognitive science, forecasting services, management science, and information retrieval systems. The recommendation process consists of three phases, i.e. information collection phase, learning phase and recommendation phase (Isinkaye et al., 2015). There are two most used recommendation techniques, collaborative filtering technique and content-based filtering technique. The collaborative filtering (CF) technique recognises the similarity between the users or items to provide recommendations. It is a domain-independent recommendation technique. Collaborative filtering techniques are further divided into memory-based techniques and model-based techniques. Content-based filtering technique takes care of the features or attributes of the items for recommendations. Instead of discovering the similarity between the users, it observes the similarity between the items by vector space model or probabilistic models. Both techniques are associated with limitations like a cold-start problem, data sparsity problem, scalability, content over specialisation and synonymy.

This paper presents a comprehensive review of the literature by exploring IoT recommenders according to a technique used. We finally represent the challenges and future scope related to this area. The rest of the paper is organised as to what are IoT recommender systems and differentiates them for the traditional recommender systems, discusses the various techniques of IoT recommender systems, presents some challenges and future scope.

### **IoT RECOMMENDER SYSTEMS**

IoT generated data is dynamic and flexible, so the traditional recommendation techniques are ineffective and inefficient in IoT based services (Yao et al., 2019). IoT recommender systems are focused on recommendations of things and services (Mashal et al., 2015; Yao et

al., 2016). Recommendations in IoT reduce the personal efforts in discovering the exciting things and services according to user's personal preferences and are favourable for business enhancement and society development. IoT based recommendations require changes in the traditional recommendation methods based only on the characteristics of users and items. Kwon and Kim (2016) proposed a method by adding the characteristics of IoT in the form of social relationships between devices like POR (Partial Object Relationship), SOR (Social Object Relationship), C-LOR (Co-location Object Relationship), OOR (Object-Object Relationship), C-WOR (Co-Work ObjectR) in the traditional recommendation methods to configure a hybrid recommendation approach. Embedded systems of IoT scenarios can utilise the benefits of profile-driven and context-aware recommendations. The prediction quality of the existing recommendation algorithms is also improved by the availability of IoT characteristics and orthogonal data sources (Felfernig et al., 2017). Saleem et al. (2017) proposed a three-layer model by exploiting social IoT for recommendation services among various application domains of IoT. Cha et al. (2017) explained how the IoT platform is helpful for the collection of streaming and user contextual data for designing a real-time recommender system by geofencing. The experiment results of the proposed prototype model show that recommendation takes more time due to the usage of geofencing rather than using beacons.

A novel recommender system in the IoT was introduced by Frey et al. (2015) that deduce the users consumed physical objects by exploring the installed apps in their smartphones or tablets to build a digital inventory to recommend the physical things to new users. The proposed recommender system consists of two parts. The first is an app for data collection and sending recommendation notifications. The second is a server for data processing and to compute personalised recommendations. Sawant et al. (2017) introduced a basic architecture of IoT and CPS (Cyber-Physical System) with decision-making capabilities that provide recommendation services through SMS or Email. The proposed system architecture comprises four layers: selection layer, network layer, service layer and application layer. First the selection layer selects and filters the sensible data provided by users. Then, the network layer, broadcast the selected data to the Service layer. Third, the service layer processed the data using web services and feed the data to the application layer. Finally, the application layer interact with the users and suggest the services. Despite the remarkable advancements and research from the last decade IoT recommendations are complex as compared to the traditional (2D) recommender systems (Pratibha & Kaur, 2018). Table 1 explains how IoT recommender systems are different from traditional recommender systems (Yao et al., 2016; Yao et al., 2019; Felfernig et al., 2019; Felfernig et al., 2017).

Table 1

*Differences between IoT Recommender Systems and Traditional Recommender Systems*

| Sr. No. | Parameters                  | IoT Recommender Systems (IoT RS)                    | Traditional Recommender Systems (2D RS) |
|---------|-----------------------------|---|---|
| 1.      | Recommended Object          | Things, Services                                    | <b>Books, Movies, websites</b>          |
| 2.      | Dynamicity                  | Dynamic   | <b>Static</b>                           |
| 3.      | Heterogeneity and Diversity | Heterogeneous and more Diverse                      | <b>Homogeneous and less diverse</b>     |
| 4.      | Context-aware               | Yes, need contextual information                    | <b>Context less</b>                     |
| 5.      | Accuracy                    | Less  | <b>More</b>                             |
| 6.      | Security and Privacy        | Should be more aware                                | <b>Less Aware</b>                       |
| 7.      | Multimodality               | Interactive, Persuasive and Multimodal interface    | <b>Singleton Interface</b>              |
| 8.      | Distributed Nature          | Yes   | <b>Centralised</b>                      |
| 9.      | Spontaneity                 | More  | <b>Less</b>                             |
| 10.     | Spatiotemporal Correlation  | Yes, need to be taken care between things and users | <b>Need not to be taken care</b>        |
| 11.     | Scalability                 | Yes   | <b>No</b>                               |
| 12.     | Data Source                 | Streamed and orthogonal                             | <b>Flat and Fixed</b>                   |

## TECHNIQUES FOR IOT RECOMMENDER SYSTEMS

Many IoT RS techniques and models are proposed and implemented in the literature for things and services recommendations. To the best of our understanding, the paper has taken care of all available algorithms, models and approaches in IoT recommendations. We categorise the literature into the IoT recommendation techniques such as context-aware, knowledge-based, collaborative filtering-based, group-based, correlation-based, machine learning-based, graph-based and trust-based. The categorisation is according to the dynamic perspective taken care of in the purposed models of IoT recommender systems. The main dynamics for the recommendation techniques in IoT are context-awareness, characteristics of IoT things and applications, trust, IoT data representation and Social IoT.

Collaborative Filtering (CF) is one of the famous approaches used to design a recommender system. It involves depending on the history of users. Besides the challenges faced by the CF algorithms, they are used by some recommendation models in the IoT context. These days, RS are no longer personal recommender systems. Instead, they list

out the recommendations to a group of users and leads to group recommender systems. We consider the IoT RS, which exploits a group's desires and preferences within some correlation and gives suggestions to the whole group under Group-based Recommender Systems. The IoT RS, which exploit the functional knowledge about users, things (devices), IoT services and their identified relationships, are considered under the Knowledge-based IoT recommender Systems. We also put the ontology-based RS in this category, as ontology is the formal knowledge representation to build the IoT RS. Many frameworks of IoT RS have used the context-awareness of geographical locations, state of people, locations of physical objects, the identity of users, and leads to Context-aware IoT RS. Although Context-aware RS faces several challenges like context discovery, privacy issues and security threats, some researchers have used contextual information to develop the IoT-based Recommender Systems.

Some developed recommendation models used the graphical database model to represent the structural schema and relations among data. We consider such models under the Graph-based IoT recommender systems. Graph-based recommendation models have the capability of resolving scalability issues. Furthermore, the social networking application to the IoT creates the scope for a social relationship among things. The system models which suggest the recommendations by introducing the concept of socialisation between things, users and services are considered under the Correlation-based IoT recommendation systems. Machine Learning is an emerging and most desiring field to develop recommendation systems using human learning and real-world knowledge. With hybridisation, Machine Learning was also utilised by many traditional recommender systems to optimise their accuracy. Traditional recommendations techniques are not able to learn from the dynamic human activity pattern in IoT. However, machine learning with deep learning and reinforcement learning give promising opportunities for developing IoT RS. Many developed IoT RS models have extensively used machine learning, so we categorise them under the Machine learning-based IoT Recommender Systems. Figure 1 explains the taxonomy of the IoT recommender systems. The under given section will describe the techniques mentioned above by taking care of proposed models of the literature.

### **Context-aware IoT Recommender System**

Context-aware recommendation techniques in IoT uses the contextual information regarding things, users, services and relationship. Integrating contextual information with traditional recommendation technologies results in multidimensional recommender systems with improved, efficient and accurate recommendations. Yavari et al. (2016) proposed an IoT based contextualised technique that involves Internet-scale data for fast decision making to provide personalised information to the users. Salman et al. (2015) suggested a proactive real-time context-aware RS that provide multi-type recommendation using neural

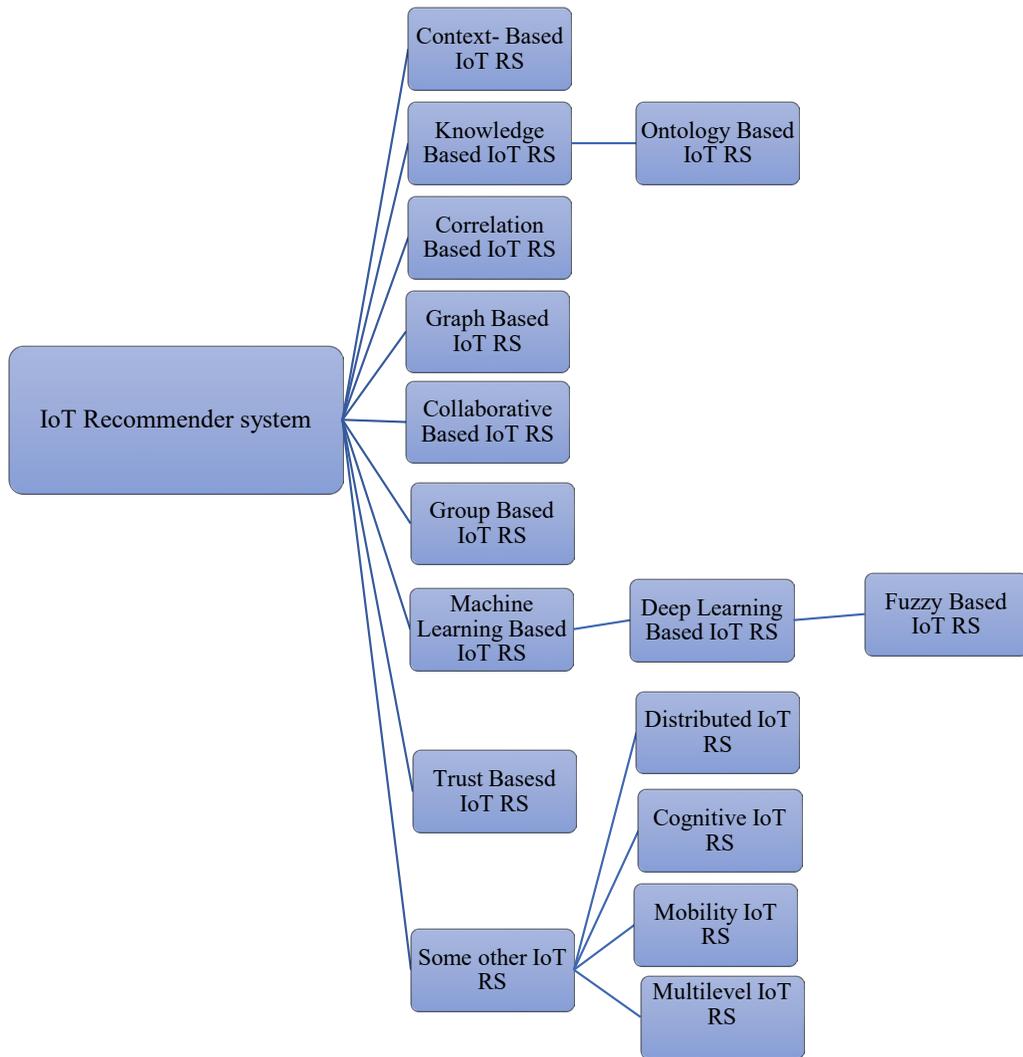


Figure 1. Taxonomy of IoT Recommender Systems

network reasoning power in the IoT paradigm. Twardowski and Ryzko (2016) presented a Multi-Agent System architecture for Big Data processing based mobile context-aware RS. Baltrunas et al. (2011) proposed Matrix Factorisation based context-aware RS, which provide interaction between items and context with less computational cost.

A scenario-based e-commerce recommendation model is introduced by Wu et al. (2019), based on customer interest and scenario-based contextual information in an IoT environment. Distributive cognitive theory is used to differentiate the sensitive scenario by establishing a multi-dimensional customer interest feature vector. Experimental result

shows that the model gives better recommendation accuracy and adaptable for high-quality recommendation services. Ravi et al. (2019) proposed a model CHXplorer composed of two building blocks, i.e., information management and multipurpose intelligent system. It is a mobile decision-support tool that provides practical recommendations to cultural heritage visitors.

Amato et al. (2013) proposed a Context-Aware Recommender System (CARS) model, assisted by users' preferences and multimedia information extracted from a mobile environment of cultural heritage. This model uses the hybrid recommendation technique combined with collaborative filtering over content-based filtering with similarity matrix k-nearest neighbour. Abu-issa et al. (2020) presented the design and implantation of a mobile-based application known as multi-type proactive CARS. It includes the user context and can provide multi-type recommendations. Zia et al. (2018) proposed an agent and context-based model for recommendations on Internet of vehicles scenario by using social and contextual network information. Context-awareness is a significant factor to upgrade the accuracy and efficiency of IoT recommender systems. Table 2 describes the context-aware recommender systems for IoT based scenarios.

Table 2

*Context-aware IoT Recommender Systems*

| <b>Model</b>   | <b>Authors and Year</b> | <b>Technique used</b>                    | <b>Data set</b>   | <b>Domain</b>                                    | <b>Metrics</b>        |
|--|-------------------------|--|---|--|-----------------------|
| Contextualised Smart Parking Recommender (CSPR)                | Yavari et al. (2016)    | Context based filtering and aggregation  | Melbourne City dataset  | Smart city, parking space recommendation service | Query processing time |
| PMCARS (Proactive Multi-type Context-Aware Recommender System) | Salman et al. (2015)    | Collaborative filtering, Neural network  | Modeled data  | Gas station and Restaurant recommendation        | MSE (Accuracy)        |
| RTRS (Real-time recommender system)                            | Cha et al. (2017)       | Collaborative filtering, Cloud computing | Tourism data from city of Saint John in New Brunswick, Canada | Smart Tourism                                    | Standard deviation    |

Table 2 (Continued)

| Model                           | Authors and Year            | Technique used  | Data set         | Domain                         | Metrics              |
|---------------------------------|-----------------------------|---|------------------|--------------------------------|----------------------|
| MCARS (Mobile Context Aware RS) | Twardowski and Ryzko (2016) | Matrix-factorisation, Stochasting Gradient Descent (SGD)  |                  | Dietary/Fitness recommendation |                      |
| SERABCI                         | Wu et al. (2019)            | Nearest Neighbour-based Collaborative filtering algorithm | B2C-Platform-Set | E-commerce                     | MAE                  |
| CHXplorer                       | Ravi et al. (2019)          | User-based collaborative filtering                        |                  | Cultural Heritage              | Precision and Recall |
| MPCARS                          | Abu-issa et al. (2020)      | Classification (Naïve Bayes classifier)                   | Survey based     | Smart city                     | Accuracy             |

### Knowledge-based IoT Recommender System

The knowledge base is the store of rules, facts and assumptions in a structured or unstructured manner. It is a kind of repository enabled for searching and processing. The object model used to represent the knowledge base is called ontology. A knowledge-based recommender system (KBRS) provides the recommendations by inputs user specifications, item attributes and domain knowledge. KBRS are generally used when sufficient ratings are not available for luxury things, financial services and real estate. Moreover, help to compensate for the Cold-Start problem (Aggarwal, 2016). Based on interface and knowledge, the knowledge base recommender systems are classified into two types, i.e., constraints-based (rule-based) recommender systems and case-based recommender systems. Constraints-base RS takes inputs in the form of constraints regarding item attributes and is matched with domain-specific rules to the user requirements. In Case-based RS, the user describes the specific cases as anchor points or targets. Similarity metrics are used on the item attributes to identify the similar items with the specified cases.

The result can be assumed as the new anchor point with interactive modification by the users to make the recommendation process more interactive. A utility-based recommender system is just a special case of KBRS. A utility function is deployed to calculate the liking probability of an item by the user. The selection of the appropriate utility function is the

main challenge, and the utility value for the target user is selected by the function called a priory. We consider the Ontology-based IoT recommender systems under the Knowledge-based IoT recommender systems as ontology is just an object-based description of the knowledge base. Ontology-based recommender systems are KBRS, which use ontological knowledge representation. Tarus et al. (2017) explained with their literature review that aggregation of the domain knowledge using ontology overcomes some of the limitations of conventional recommender systems.

Lee et al. (2019) proposed a recommendation model based on IoT users' implicit requests and information curation. The introduced model is divided into two parts. The first part reveals the requestor's desire by collective intelligence. The second part displays the recommendations compellingly. Franco (2017) explored an automatic and learning-based personalised recommender system using association rule mining techniques to recommend automation rules and feature the Smart Home applications (Franco, 2017). The rule is composed of trigger (only one), action (one or more) and state checks (zero or more). The proposed model includes the generalisation of rules, a similarity-threshold parameter to check the similarity of generalised rules (templates) and the application of an association rule mining algorithm (Apriori). The author developed a baseline non-personalised recommender system for evaluation and compared it with the proposed system with metrics Precision, Recall, F1-Score and Coverage. Subramaniaswamy et al. (2019) proposed a personalised recommender (ProTrip RS) for travellers by considering the user's parameters like travel sequence, motivations, actions, opinions and demographic information. The system has the capability of food suggestions based on personal choices, nutrition values and climate attributes, favourable for travellers with long term diseases and who follow a strict diet.

Recently Anthony Jnr (2020) suggested a Case-Based Reasoning (CBR) technique develop a recommender system for sustainable smart city planning. Case-based reasoning is a knowledge-based system that using similar prior cases to assess, solve or deduce the given problem. CBR uses predefined matching algorithms for searching similar cases from the case-based library. A typical CBR cycle is comprises of four phases: case retrieving, problem solution with a case, revise solution and retain the solution as a new case. Selvan et al. (2019) propose a system to develop fuzzy ontology-based RS to recommend drugs and food for diabetic patients using Type-2 fuzzy logic. The system was utilised by considering the uncertainty and heterogeneity attached with chronic patient's data collected by mobile and IoT devices. Table 3 explains some knowledge-based IoT recommender systems.

Table 3  
Knowledge-Based IoT Recommender Systems

| Model  | Authors                       | Technique used                               | Data set  | Domain                       | Metrics                                     |
|--|-------------------------------|--|---|------------------------------|---|
| <b>An approach for better recommendation by revealing hidden desire and information curation</b> | Lee et al. (2019)             | Normalised Weighted Vector-mapping algorithm | Internet social community sites like GroupOn, Opentable       | E-commerce                   |   |
| <b>IoTRS for Automation Rules</b>  | Franco (2017)                 | Apriori (Association rules mining Algorithm) | Muzzley automation rules dataset                              | Smart Home                   | Precision, Recall, F1-Score and Coverage    |
| <b>ProTripRS</b>   | Subramaniaswamy et al. (2019) | Hybrid filtering (CF+CBF+KBF)                | Real climate-based dataset, food information and user dataset | E-Tourism                    | Precision, Recall, F-measure, Response time |
| <b>CBR Recommender System</b>  | Anthony Jnr (2020)            | Case based reasoning                         | Survey based data   | Smart City                   | Std. deviation, Skewness, variance          |
| <b>FOPR for IoT</b>  | Selvan et al. (2019)          | Type-2 Fuzzy logic                           | Chronic patients' dataset                                     | IoT based Health care system | Recall, Precision, Accuracy, F-measure      |

### Correlation-based IoT Recommender System

Correlation is defined as a mutual association between two or more things. The convergence of social networks and IoT develop the Social Internet of Things (SIoT). The SIoT adds correlations in practice for representing the interdependencies of the things or objects (devices), users and services. The inclusion of social networking aspects in the IoT discovers the automatically social relationship between objects and services to enhance information sharing, support for new applications and provide trustworthy network solutions (Roopa et al., 2019).

Saleem et al. (2017) developed a recommendation service to exploit SIoT by inferencing data from various IoT objects and services. The proposed framework is divided into three layers viz. perception layer, network layer and interoperability layer. The author discussed some implementation challenges in realising a proposed model, interoperability, trust, privacy, security, network management and navigability. Kang et al. (2016) proposed a social correlation group-based recommendation technique (SRS) by generating a target group with social correlation in services. The model uses the feature of social interest similarity and principles of CF and CBF. Authors define the social correlation group using their previous study and select the correlated nodes for the target service. The architecture of SRS consists of the Data Aggregation function to aggregate the data and the Data Abstraction function to build abstract data structure. Aggregated and Ontology Graph Manager manages abstracted data. Social correlation group is generated by Target Group function explained by the following Equations 1 and 2:

$$P(e1, c) = ve1 + \frac{\sum_{e2=1}^n sim(e1, e2)(ve2, c - ve2)}{\sum_{e2=1}^n mod(sim(e1, e2))} \quad (1)$$

Where,

$$sim(s, n) = \frac{\sum ps * pn}{mod(ps) * mod(pn)} \quad (2)$$

In this  $sim(s, n)$  means how service requirement is close to user  $n$  and  $P(e1, c)$  is predicted correlation for entity  $e1$  on content  $c$ .

Forouzandeh et al. (2017) proposed a recommender system based on the relationship between users, objects, services and recommended an IoT device. Yao et al. (2016) discuss the solution of things recommendations problem in IoT by defining new properties of things of interest and build a framework based on unified probabilistic factors by putting together relations of IoT heterogeneous entities. Table 4 explains the correlation-based IoT Recommender Systems from the literature.

Table 4  
Correlation-based IoT Recommender Systems

| Model                                   | Authors                   | Technique used                                    | Data set  | Domain   | Metrics  |
|---|---------------------------|---|---|--|--|
| <b>SRS</b>                              | Kang et al. (2017)        | Collaborative filtering + Content-based filtering | MovieLens (SNS Domain+ IoT service+ media service | SIoT Applications                              | Prediction accuracy (MAE), Preference evaluation (MV), Hit ratio |
| <b>IOTSRS</b>                           | Forouzandeh et al. (2017) | Collaborative filtering (Pearson correlation)     | Telus, Lbelium, BlueRover (IoT service companies) | IoT services                                   | Precision, Recall, F-measure, RMSE                               |
| <b>ToI Recommendation by LHR in IoT</b> | Yao et al. (2016)         | Probabilistic matrix factorization                | WS university's CASAS dataset                     | Thing recommendations (E-commerce, Smart home) | MAE (Accuracy)   |

## Graph-based IoT Recommender System

Graph-based Recommender Systems use undirected, highly connected graph that correlate between things as edges and items as nodes (Lee & Lee, 2015). Graph-based RS works in two stages which are Pre-processing Stage and Recommendation Stage. Graph-based RS has been used in different domains, mainly for tag recommendations by constructing a graph, users and resources. FolkRank is a well-known approach for tag recommendations designed by adapting Google's PageRank Algorithm. In traditional recommender systems, graph-based recommender system represents item and the user as a node in a graph by user set  $U = \{u_1, \dots, u_n\}$  and item set  $I = \{i_1, \dots, i_n\}$  to instantiate a bipartite graph  $G = \langle V, E \rangle$  (Musto et al., 2016). There is a node for each user and item, so the total number of vertices is  $|V| = |U| + |I|$ . Undirected edges are connected between each item  $i$  and user  $u$  for users positive feedback, hence  $E = \{(u, i) \mid \text{likes}(u, i) = \text{true}\}$  *likes* is the function for positive feedback given by user to item  $i$ . Chaudhari et al. (2017) proposed a privacy-aware Graph-based recommender system by exploiting the relations of content entities from user's history and with candidate content entities. A knowledge graph is used to encode the relations between entities. The proposed approach is not domain-based and can also be used for the search.

Mashal et al. (2015) introduced a graph-based service recommender system in the IoT that recommend services in applications like health care, energy monitoring. Weighted undirected tripartite graph-based model is used to define the IoT by tuple  $I = (U; S; O; Y)$ , here  $U = \{u_1, \dots, u_m\}$  a user set,  $S = \{s_1, \dots, s_k\}$  service set,  $O = \{o_1, \dots, o_n\}$  object set with  $k$  service,  $m$  users and  $n$  objects. Ternary relation of these components is represented by  $Y$  is the subset of  $U * S * O$ . Vertices ( $V$ ) are composed of services, objects, users and edges by  $E = \{\{u, s\}, \{s, o\}, \{u, o\} \mid \{o, s, u\} \text{ belongs to } D\}$   $D$  is a dataset. The weight value of edges is calculated by  $\leftarrow dAw + (1 - d)p$ , where  $A$  is the adjacency matrix,  $p$  is random suffer,  $d$  is a constant to control the random suffer from 0 or 1. Palaiokrassas et al. (2017) presented an innovative architecture that combines big data and user-generated data to make efficient recommendations using the Neo4j graph database for smart city-based applications.

Nizamkari (2017) presents a scalable recommendation technique by incorporating trust for service selection in SIoT. The result shows that the inclusion of trust into the recommender system increases coverage and accuracy compared to the traditional CF recommendation system. However, the proposed model suffers from a cold-start problem present in all types of CF recommender systems. Finally, Mashal et al. (2016) investigate that graph-based recommendation algorithms can give better results to develop an efficient and accurate recommender system for IoT to service recommendations and leverage the region of recommendations algorithms. Table 5 explains the graph-based recommender systems in IoT.

Table 5

*Graph-based Recommender Systems*

| <b>Model</b>  | <b>Authors</b>              | <b>Technique used</b>  | <b>Data set</b>            | <b>Domain</b>                    | <b>Metrics</b>                      |
|---|-----------------------------|--|----------------------------|----------------------------------|-------------------------------------|
| <b>Undirected tripartite graph-based RS</b>             | Mashal et al. (2015)        | FolkRank (graph-based algo)                                      |                            | IoT based any application domain | <b>MAE, RMSE, Recall, Precision</b> |
| <b>An IoT architecture personalised recommendations</b> | Palaiokrassas et al. (2017) | Vector based Cosine or Euclidean similarity matrix               | Neo4j, Node-Red data store | Smart cities                     |                                     |
| <b>GB trust enhanced RS</b>                             | Nizamkari (2017)            | Collaborative filtering (Pearson correlation)                    | LibimSeTi                  |                                  | <b>MAE, RMSE, Coverage</b>          |
| <b>IoT SRS</b>  | Mashal et al. (2016)        | MPS, MPSU, MPSO, MPSUO, Servrank, User-based CF, object-based CF | Libeliu, Telus, BlueRover  | IoT service domain               | <b>Recall, Precision</b>            |

**Collaborative IoT Recommender System**

The traditional collaborative recommender systems out of the IoT context use the item rating explicitly mentioned by the user to find similar users (user-based technique) or similarities between the items (item-based technique). Nevertheless, Muñoz-Organero et al. (2010) proposed a system that uses the location and time of user and things instead of item rating to make collaborative recommendation compatible for IoT scenarios. The author uses the Pearson correlation similarity metric. The experiment results show that user-object interaction time and user locality are better than user rating in an IoT based environment. Choi et al. (2015) introduced a recommendation model based on Bandwagon Effect by exploiting the IoT information regarding item selection history without any extra actions. Bandwagon Effect shows its usefulness in conventional movie recommendation systems and is now also used in IoT recommender systems. The phenomenon of Bandwagon shows that fashionable information plays an important role to affect the personal choices for item selections, which means a person wants the same item when most people also want it.

Erdeniz et al. (2019) proposed a new recommender system for mobile health applications enabled by IoT, which gives recommendations about activity plans for improving individual health conditions. Table 6 represents the collaborative recommender systems for the IoT domain.

Although many studies used the CF technique, IoT RS based on CF suffers from some potential problems. These techniques are inefficient for IoT-based recommendations. The problems are scalability, cold start and data sparsity. IoT recommendation techniques should be scalable to deal as fast as possible with extensive dynamic data. A cold start problem occurs when new devices are added to the system without users' ratings. As the number of things increases, data sparsity problems can exist and affect the accuracy of IoT RS.

Table 6  
*Collaborative Recommender Systems*

| Model   | Authors                      | Technique used                                | Data set                            | Domain                           | Metrics                         |
|---|------------------------------|---|-------------------------------------|----------------------------------|---------------------------------|
| <b>CRS based on STS</b>                                   | Muñoz-Organero et al. (2010) | Pearson similarity metric                     | Synthesised Data set                |                                  | <b>Mean, Standard deviation</b> |
| <b>Bandwagon Effect based Recommendation MODEL (BERM)</b> | Choi et al. (2015)           | Collaborative filtering                       | GroupLens movie dataset             | E-Marketing                      |                                 |
| <b>IoT RS for m-health (Virtual Coach)</b>                | Erdeniz et al. (2019)        | Collaborative filtering (K-nearest neighbour) | Sample dataset from Quantified-Self | IoT enabled m-health application |                                 |

### Group-based IoT Recommender System

A group-based recommender system provides recommendations to all the group members. The group is made by users with similar preferences, interests or likes. Shang et al. (2014) proposed a framework of a group-based recommender system beyond the anonymity and personalisation towards privacy preservation. The structure of the proposed model is divided into stages: preference exchange between peer to peer, preference aggregations within a group, inter-group recommendations, and local and personal recommendations. The last stage includes recommendations made by incorporating group social information and item content. So, groups can preserve individuals' private preference data by natural protection mechanisms from service providers. Elmisery et al. (2017) proposed a privacy-aware group-based RS for automatic finding interest groups in multimedia services with the

introduction of a middleware based on fog computing runs at the end-user side to exchange the user information for creating interest group and to facilitating recommendations without revealing his preference to other users. Generally, creating an interested group requires consumer's data that is a threat to their privacy.

Lee and Ko (2016) developed a recommender system for service selection to users in IoT enriched environment. However, aggregation of the user's preferences of a group is not suitable for an IoT environment, so the authors' design a user-based CF approach by considering a member organisation for the new neighbour group selected by MOGS (Member Organisation based Group Similarity) metrics such as common member-based, group size-based and member preference-based. Wang et al. (2020) described an average strategy-based group recommender system with preferential differences between group members using the trusted social network for preference corrections. Table 7 describes the IoT based group recommender systems.

Table 7

*Group-based Recommender Systems*

| <b>Model</b>   | <b>Authors</b>     | <b>Technique used</b>              | <b>Data set</b>  | <b>Domain</b>           | <b>Metrics</b>   |
|--|--------------------|------------------------------------|------------------|-------------------------|------------------|
| <b>Service Recommendation for UG in IoT using MOGS similarity metrics</b>  | Lee and Ko (2016)  | User-based collaborative filtering | Synthesised data | IoT based application   | <b>Precision</b> |
| <b>GRS based on MPTSN (Member's preference for Trusted Social Network)</b> | Wang et al. (2020) | RM based on IS, MF, IP, IFD        | FilmTrust        | IoT enabled Environment | <b>MAE</b>       |

### **Machine Learning-based IoT Recommender System**

Machine learning is the ability of a computer system to automatically acquire knowledge to find solutions by accessing, looking, observing and recognising patterns of data from the database. Machine learning-based systems learn from past experiences without preprogramming and human interventions. There are two types of machine learning algorithms supervised (with labelled training data) and unsupervised (without labelled training data). Supervised learning is guided by a supervisor (trainer), data set acts as a supervisor to train the model. Regression, classification, decision tree, random

forest technique comes under supervised learning. In unsupervised learning, the model automatically learns patterns and relationships by observing the data structure. Clustering and association techniques come under unsupervised learning. Semi-supervised learning comes in the middle of unsupervised and supervised. The model is trained by combining the small labelled data with large non labelled data. Reinforcement learning sticks to learn from its experiences by taking steps when training data is not present.

Deep learning is an emerging machine learning technique that uses artificial neural networks and precisely assigns credit weights to the neural network layers to manifest the desired behaviour. Deep learning enables multiple processing layer computational models to learn from data representation in multiple abstraction levels. Deep learning also shows its potential in recommendation techniques with enhancing the efficiency and accuracy of RS. Recommender systems are flourishing by emerging deep learning techniques. Hence, deep learning pervasive nature help lifts the information retrieval systems and recommender systems (Ouhbi et al., 2018). Milano et al. (2020) present a literature review for ethical challenges for recommender systems like appropriate content, privacy, autonomy and personal identity, opacity, fairness and social effects.

Jabeen et al. (2019) proposed an IoT and community based efficient recommender system for diagnosing cardiac diseases and gave suggestions about the dietary and physical plan. Sewak and Singh (2016) suggested upgrading conventional recommenders into Optimal State recommender solutions to cope with the upcoming era of pervasive IoT and smart wear. The proposed architecture includes distributed and real-time machine learning for IoT based data to mitigate the challenges for optimal state recommender systems. The architecture uses some distributed advanced machine learning algorithms like distributed mini-batch SGD (Stochastic Gradient Descent), distributed Kalman filters. As all the components of the architecture are open source, they can run on the cloud for high flexibility, scalability and low cost that can be applied to IoT based industries. Barbin et al. (2020) proposed an RS based on the user's profile and service interest by making a decision tree for user classification. Ensemble learning techniques combine and rank the recommender system output, which improves the accuracy and efficiency of the recommendation technique. The result shows that the presented models enjoys higher accuracy than other recommendation model based on exact methods.

Guo and Wang (2020) proposed a deep Graph NN based social recommendation (GNN-SR) that deal with the challenge of neglecting the item's features correlation that can influence social group topologies. Their existing approaches for social recommendation use the quantified correlation between user preferences and social connections. Graph neural network method is used to encode user feature space graph and item feature space graph which is implanted into two latent factors of MF (Matrix Factorisation), used to resolve sparsity of item-user rating matrix. Huang et al. (2019) described a new

Multimodality Representation Learning-based Model (MRLM) to overcome the challenges of multimodality and heterogeneous information description of IoT items. The proposed model trains two submodules. First is GFRL (Global Feature Representation Learning) to represent the global features of users and items and accomplish three tasks, namely SoftMax classification, microscopic verification and triplet metric learning. Second is MFRL (Multimodal Feature Representation Learning) to refine global features of the item and produce multimodal final features from multimodal information description. MRLM consists of two phases, i.e., Data Processing and Model Training.

Experiments show the effectiveness of recommendations in IoT on two real-world data. First, Iwendi et al. (2020) propose a deep learning-based solution on health-oriented medical data for food recommendations to patients based on diseases and personal health features (weight, age, gender, cholesterol, fat, protein) implanting machine and deep learning algorithms. The Internet of Medical Things (IoMT) features is analysed and encoded before submitting to deep learning models. Second, Gladence et al. (2020) designed an RS for disabled and older people to provide home management assistant. NLP (Natural Language Processing) plays a vital role by acting as an interface between user and machine and enable the system to be controlled by the user's command. The proposed system is composed of integration of machine learning, cloud platform (Python-anywhere) and IoT. The framework comprises four layers, namely devious environment, cloud computing, and LAN server with Application Programming Interface for AI and smart devices. Table 8 describes Machine learning-based IoT recommender systems.

Table 8

*Machine learning based IoT Recommender System*

| <b>Model</b>          | <b>Authors</b>         | <b>Technique used</b>  | <b>Data set</b>            | <b>Domain</b>                       | <b>Metrics</b>                    |
|-----------------------|------------------------|--|----------------------------|-------------------------------------|-----------------------------------|
| <b>IoT based EHRS</b> | Jabeen et al. (2019)   | Classification, Advice-based collaborative filtering                       | Hospital dataset           | IoT based healthcare system         | MAE, Precision, Recall, Accuracy  |
| <b>OSRS for IoT</b>   | Sewak and Singh (2016) | Supervised machine learning  |                            | IoT Based services, Smart Marketing |                                   |
| <b>EISRS</b>          | Barbin et al. (2020)   | Classification (Binary decision tree), Association, Ensemble learning algo | Telus, Libelium, BlueRover | IoT service domain                  | Precision, Recall, F1-score, RMSE |

Table 8 (Continued)

| Model                        | Authors                | Technique used  | Data set                    | Domain                       | Metrics                                 |
|------------------------------|------------------------|---|-----------------------------|------------------------------|---|
| <b>GNN-SoR for IoT</b>       | Guo and Wang (2020)    | Matrix factorisation, SGD (Stochastic gradient descent) | Epinions, Yelp, Flixter     |                              | RMSE, MAE, NDCG                         |
| <b>MRLM</b>                  | Huang et al. (2019)    | Multilayer CNN, Cosine similarity                       | MovieLens-20M, BookCrossing |                              | Recall, AUC (Area under ROC)            |
| <b>IoMT-APDRS</b>            | Iwendi et al. (2020)   | LSTM deep learning                                      | Health-base medical dataset | Smart healthcare             | Recall, Accuracy, Precision, F1-measure |
| <b>RSHA using IoT and AI</b> | Gladence et al. (2020) | NLP (Natural Language Processing)                       |                             | Smart Home Automation System |   |

### Trust Aware IoT Recommender System

Trust is defined as reliance on the ability, integrity and nature of a thing (object), service or user necessary for social transactions in an IoT environment. Cryptography methods are not efficient to guarantee data/user security, trustworthiness and resistance in IoT based services (Mohammadi et al., 2019). So, for achieving the network's security trust evaluation, a rational recommendation for estimating friend node reliability should be employed at the node level. Furthermore, traditional security mechanisms cannot detect disrupt and malicious transmission in IoT scenarios. So, trust models are used to detect delusive behaviour by distinguishing honest nodes incorporated in the IoT devices.

Trust-based Recommender systems are developed to improve the recommendation quality by including the trustworthiness of users in the collaborative filtering technique. Two types of trust computation models –the reputation trust model and the relationship trust model, are incorporated in the trust-based recommender systems. Trust aware RS for IoT helps the users find reliable services by searching the entire scale-free trust network with high computational cost. Yuan et al. (2013) proposed an efficient search model called S\_Searching based on the scalability freeness parameter of trust networks. A Skelton is made by choosing the highest degree nodes globally, and searching mechanisms for recommenders are conducted with this Skelton. With less computational cost and complexity, the S\_Searching mechanism can find trustable recommender services. Many

Trust-based Recommendation models are not included in our literature survey because there is already a review paper for Trust-based recommendation systems in the IoT (Mohammadi et al., 2019).

### **Some Other IoT Recommender Systems**

There are also some proposed models in literature with different recommendation techniques used in IoT based domain. Forestiero (2017) suggests a multi-agent-based RS utilising self-organising strategies and decentralisation for things recommendations in IoT. Locality preserving hash function maps similar things into similar bit-vectors managed by a cyber agent and converted based on an ad-hoc probability function. Result explains that the recommendation is fast, and the algorithm is scalable with constructive reorganisation for descriptors. Hamlabadi et al. (2018) proposed a framework of the Cognitive Recommender System (CRS) in the IoT. A cognitive system learns by employing in an unknown environment to improve its performance. The framework is distributed in three layers, namely Requirement layer, Thing System Layer (TSL), and Cognitive Process Layer (CPL). The proposed framework is flexible, cognitive, general-purpose and enabled for sharing. Saghiri et al. (2018). Suggested a recommender system on the IoT framework based on blockchain technology and cognitive systems. This framework consists of a requirement layer, cognitive process layer and things management layer embedded by IoT and blockchain technology.

Chirila et al. (2016) developed a recommendation mechanism for service recommendations to IoT devices enabled by web service interfaces. The proposed model uses broker-based architecture with semantic similarity-based filtering and clustering technique. Di Martino and Rossi (2016) proposed a Mobility Recommender System (MRS) based on scalable and distributed IoT architecture for ITS (Intelligent Transport System). The proposed architecture utilises road infrastructure based heterogeneous data (digital map and parking info) for recommendations.

Matsui and Choi (2017) proposed an RS that suggests indoor comfort products by exploiting HEMS (Home Energy Management System) data like indoor humidity, temperature, luminance, power consumption, and clothing quantity. Generally, people are not aware of the services related to the smart objects they purchased, so an RS can facilitate by recommending IoT services to grasp the connected smart objects (Noirie et al., 2017). Mashal et al. (2020) develop a recommendation system using a decision-making approach based on hybrid multi-criteria to suggest the most suitable IoT application. Additive weight methods and analytical hierarchy processes are used in the decision-making process. To overcome interoperability issues in IoT semantic web has been recognised as an emerging technology for service discovery (Kolbe et al., 2019). Cao et al. (2019) proposed a QoS (Quality of Service) aware service RS based on factorisation machine and relational model

to find a suitable web application programming interface for developing IoT mashup applications. Yan et al. (2019) proposed SIoT-SR (Service Recommendation) by adopting LSH (Locality-Sensitive Hashing) forest algorithm and collaborative filtering technique to discover the QoS data. It is a distributed approach and can face the privacy leakage problem. Hence, authors select LSH forest with self-correct parameters ability to enhance privacy, efficiency and accuracy.

## **DISCUSSION**

In the last few years, there is an increase in applications of recommendation technologies for IoT application areas like smart marketing, smart home, smart tourism, smart healthcare systems, and smart cities development. We reviewed the main trends and techniques used by the published studies from 2013 to 2020. Some studies have made use of conventional recommendation approaches. However, there is a need for improvements in conventional methods to cope with the dynamic, heterogeneous and distributed IoT environment. Deep learning and reinforcement learning algorithms can provide promising results by capturing the users' temporal intentions.

As IoT Recommender Systems are in their infancy, there is a need to resolve the security and privacy issues to protect malicious activities over users' data. In most of the developed models in the literature, simulated data is used, as the accessing of real-time data is too complex. In most models, matrices like MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), Precision and Recall are used to quantify the accuracy of the IoT RS. However, there is a lack of evaluation measures to quantify the IoT RS's productivity, diversity, scalability and adaptability. Therefore, IoT Recommendation techniques should evaluate the above parameters to be more applicable in IoT-based real-time application scenarios.

## **CHALLENGES AND FUTURE SCOPE**

IoT technology enables various physical devices to talk and interact by creating new opportunities in many application domains. IoT technologies are desirable of an efficient and effective searching paradigm for helping users in extracting, visualising, recognising, decision making from non-standardised and high dimensional data. Therefore, there is a need for information filtering or decision-supporting tools to solve the information overloading problem in IoT based scenarios. However, developing an efficient, accurate and effective recommendation technique to meet users' desires faces many difficulties due to IoT characteristics like heterogeneity, real-time communication, scalability, mobility, dynamicity and correlation with things. Due to the problems mentioned above, recommender systems in IoT have not yet acquired as much effectiveness as they acquire in

non-IoT domains. Recommendations in IoT are dynamic, distributed, more context-aware and heterogeneous as compared to the traditional recommendations. Moreover, meeting these recommendations is a big challenge for the developers.

Instead of the above-said features of IoT based recommendations, they should also be persuasive, security and privacy-aware and interactive with a multimodal interface. Integration of the features mentioned above in the conventional recommendation techniques requires a more profound knowledge of the emerging trends (Deep learning, SIoT, ontology-driven knowledge base). Consideration of the SIoT for leveraging the heterogeneous relations of things with users, users with services, things with things and services with things is a good choice for extracting the user's preferences and choices. Nevertheless, implementation of SIoT based recommendations faces challenges like interoperability, trust and security, data discovery, social network management, self-healing and network navigability for streaming services (Saleem et al., 2017). Some researchers proposed context-aware recommender systems to incorporate contextual information in IoT recommendations. However, CARS in IoT also faces some issues: an accumulation of adequate data, context factor discovery, shortage of datasets availability, proactively informational filtering and privacy of users' contextual information. (Pratibha & Kaur, 2018). Due to the limited computational power of IoT devices, recommendation algorithms are located in clouds to support IoT apps recommendations and IoT workflows recommendations. For the recommendations of resource balancing in a particular IoT application domain, reconfiguration support recommendation algorithms should be deployed on the gateway only. For both purposes, the scalability of the recommendations algorithms creates an open challenge. The availability of a real IoT based dataset is also a challenge for the exact evaluation of algorithms. IoT has distributed nature and collects a considerable amount of data. However, data analysis methods of IoT scenarios are limited, so Big Data Analytics should be approached.

Hybridisations of the proposed IoT recommendations techniques like context-aware, knowledge-based, deep learning-based, trust-based, social correlation-based, group-based and graph-based and emerging technologies can lead to the solutions to some of the challenges mentioned above with improving the performance of IoT recommender systems. In the case of Internet connection failure, basic and most required functionalities should be available, so incorporating the recommendations functionalities on gateway can be a future work that leads to gateway autonomy property. Searching techniques can be combined with IoT recommendations for discovering user's preferences or implicit correlation with entities. The techniques are based on semantic analysis. When combined with the searching techniques, semantic analysis can enabled recommendation techniques and open a future direction for research. Most recommendation techniques do not force security and privacy constraints on the data. Blockchain-based cryptography has proved effective

security solutions in IoT environments. So, in future recommendations techniques based on blockchain supported distributed architecture can help in security and privacy concerns for user's collected data. Deep learning can provide customised and accurate recommendations, which is one of the emerging technologies for personalisation. Deep learning-based model can be deployed on an IoT device for edge computations or on a centralised server as a cloud-based learning model.

## CONCLUSION

IoT is an emerging technology with future possibilities of enabling a large number of diverse devices connections results in the assemblage of dynamic and versatile data. Recommendations technologies can use this data for real-time and personalised suggestions about services, things and any relevant commodity in IoT-based scenario. This comprehensive literature review paper explains the existing recommendation techniques in the Internet of Things (IoT). The last section discussed some of the open issues and future scope to cope with IoT based recommendations' challenges. In conclusion, we can say that this literature survey will benefit a new researcher by widening the frontiers of required knowledge in this research field.

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