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Research Article

RecIoT: A Deep Insight into IoT-Based Smart Recommender Systems

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Typically, Internet of Things (IoT) is perceived as the technology for connecting people, devices, vehicles, home appliances, etc., and 212 billion heterogenous devices are presumed to be connected by 2020 under its umbrella. This domain is gaining popularity worldwide because of the wave it has brought in both research and industrial sector. Smart applications of this scenario provide assistance and services to the users in smart homes, smart cities, smart retail, agriculture, healthcare, etc. However, researchers are now exploring the potential of IoT systems in other domains, one of them being recommender systems. In recent years, the focus of researchers has drifted towards utilizing recommender systems to improve offered selections to IoT users. Therefore, the aim of this paper is to study the present practices, approaches, and challenges in the aforementioned domain along with possible solutions. Briefly, the contributions of this paper are as follows: (1) providing an overview of the prevailing scenario in a range of application domains associated with IoT based recommender systems, (2) providing a framework of some real-world applications, (3) outlining key areas for the improvement towards context-aware personalized services in the future research, and (4) providing a bibliometric trend analysis prevalent in the concerned domain.

1. Introduction

The Internet of Things (IoT), also called as machine to machine communication, is an intelligent global network which connects multiple devices and helps them communicate via the Internet, following certain communication protocols [1]. These devices can be smart phones, computers, sensors, actuators, RFID tags, smart home appliances (electricity controller, TV, and heat measuring devices), and any device having a processor and internal memory [2]. With the evolution of modern technology, IoT has spread its roots in almost every field, be it smart homes, wearable devices, connected cars, smart cities, smart retail, and even smart hospitals. As per a study conducted by Gartner, the number of smart devices will increase to 212 billion by the year 2020 [3]. Since IoT has made our lives more convenient, given the automation and intelligence, soon the need for personalization of the IoT devices based on user requirements was realized. Therefore, to make the IoT more responsive and understand the context for decision-making, experts began to utilize recommender systems.

Recommender systems are software tools that confine the choices of a user from the plethora of options available and provide them with the most appropriate suggestions that fulfil their desires [4]. The first ever recommender system introduced is tapestry, developed by the Xerox Palo Alto Research Centre in 1992 [5, 6]. Since then, recommender systems have gained more popularity and trust in various internet applications like LinkedIn, eBay, Amazon, Hulu, TiVo, Pandora, Trip advisor, Yahoo, Netflix, Jester, Matrimonial sites, social networking sites, CiteSeer, and YouTube [7–9].

From artificial intelligence to information filtering, recommender systems have proven to be quite beneficial and the recent shift to IoT is no exemption either. IoT has been utilizing recommender systems for more optimized user choices based on their behaviors and preferences [2, 10]. Moreover, this collaboration is equally beneficial for both IoT and recommender systems. For IoT, personalized recommendations based on user preferences and behavior are boon, while for recommender systems, real-time based context aware recommendations using IoT devices can be generated.

Researchers have been working on both the areas since the last two decades. Currently, their interest has drifted towards combining IoT and recommender systems to get the best of both worlds. From education to healthcare, this collaboration has proven to be quite promising [2, 3]. Several review articles based on either IoT or recommender systems have been published till date. But no review article focusing on both the research domains has been published so far. Therefore, in this paper, the combined work on both the research areas has been reviewed.

This paper is organized as follows. In Section 2, a related work has been discussed. Section 3 covers the real-world applications of IoT and recommender systems. Section 4 is focused on the need for collaborating IoT and recommender systems. In Section 5, the use-case scenario of Netflix is considered to study how the collaboration might affect the level of recommendations generated. The work done combining the best features of both IoT and recommender systems has been described categorically in Section 6. Further, the recent trend analysis in the concerned domain is discussed in Section 7. Finally, the work is concluded in Section 8 along with a future scope.

2. Related Work

In this section, the existing work focused on both IoT and recommender systems has been discussed. It is not long back that the researchers started exploring the capabilities of recommendation algorithms in the field of IoT and vice versa. Since the millennial users often seek quick services, having two smart systems combined into one seems to be more promising in terms of customer satisfaction. From recommending things to the user in IoT to recommending services to the user based on IoT, this research has gained attention from researchers across the globe.

In [11], the authors studied the scope of recommending things in IoT. The authors proposed how fusing information of the user and things can result in better recommendations using a unified probabilistic based framework. The authors explored the possibilities of recommendation algorithms in [12] to implement recommendation services in IoT. A hypergraph model is proposed to connect users, objects, and services as the edges. Based on this work, it is observed that graph-based recommendation models have a promising future in the field of IoT.

The work done in [13] is focused on investigating mechanisms that might be used to select IoT-based services within a smart campus and to overcome discovery issues. Both content-based and collaborative filtering approaches are implemented to conduct the study, and the evaluation is done based on response time, recall, and precision metrics. The content-based filtering algorithm performs better with a higher ratio of appropriate services recommended in a shorter duration as compared to collaborative filtering. A weather and location aware recommender system within a universal environment is discussed in [14]. Weather statistics captured by different IoT sensors are considered as input data for generating recommendations to users residing around that region. The recommendations vary from items such as consumer merchandise, holiday destinations, and stock trends. Hidden Markov Model is employed to study and predict short-duration weather conditions and generate recommendations by analyzing the past sales trends under comparable weather circumstances in the past.

Personalization is something desirable by users across the globe, be it based on their previous activities or their current environment. IoT combined with recommender systems seems to be quite promising in achieving context-based personalized recommendations for any user, and this collaboration is currently a hot topic of research. The authors examined the usability of the bandwagon effect to build a users' preferences history-based recommender system in [15]. The study is conducted in movie domain using the GroupLens dataset, and the authors proposed to develop an IoT-based recommender system following the similar phenomenon for better results. In [16], the authors proposed a personalized novel recommender system based on publicly available data about the apps installed on a user device. The proposed system gathers information regarding the physical objects owned by a user, based on the installed apps on their mobile devices. These records are further used to create personalized recommendations for the user. A similar work is conducted in [17], where the authors proposed a novel IoT platform for supporting a real-time based recommender system. To generate context-based recommendations, geofencing is employed to obtain real-time data from user smartphones. A prototype of tourism application is developed to demonstrate the whole process of gathering the current location of the user using a GPS-enabled smart phone. Table 1 gives a detailed comparison of both IoT and recommender systems based on the requirements for their development.

3. Real-World Applications

In this section, a brief overview of the various applications of IoT and recommender systems that has been developed till date is described.

3.1. Education. Docear and CiteSeer are two of the most popular research article recommender systems. Both the systems are online repository of research articles published in various domains. The former uses content-based filtering while the latter uses both content-based and collaborative filtering approaches for generating recommendations for the user [18, 19]. There is a need for maintaining a constant communication among the knowledge professionals and their peers as suggested by Wenger in their study conducted centering the Malaysian Universities [20]. IoT systems based on real-time data are more promising in terms of providing better results. A case study conducted by He et al. to modify the core courses for engineering undergraduates is an example for the same. Lab course for embedded systems is designed by integrating IoT devices with various sensors over Zigbee network [21]. For better and efficient utilization

Table 1: Comparison of IoT and recommender systems.

	Requirements for development	
Parameters	IoT	Recommender systems
Data management	✓	✓
Data mining		✓
Internet connectivity	✓	✓
IoT devices	✓	
Machine learning/AI		✓
Power sources	✓	
Sensors	✓	
Bandwidth requirement	✓	
Remote surveillance	✓	
Knowledge base		✓
Smart phones	✓	✓

of IoT in the field of education, the concept of Green-IoT or G-IoT has been proposed [22].

3.2. E-Commerce. Amazon and eBay are probably the first sites that pop up in our head on hearing the term "E-commerce." E-commerce is nothing but a platform for vendors where they can sell and promote their products online. The aim of such sites or apps is to create a personalized online store for their customers [23, 24]. Recommendations for the customer are generated based on item-item collaborative filtering, user-user collaborative filtering, or content-based filtering or a combination of two or more approaches [25, 26]. IoT on the contrary has still not been used much in E-commerce. However, an IoT-based framework for accessing the freshness of in-transit fruits is proposed by Ruan and Shi [27].

3.3. Healthcare. E-healthcare systems can be informative or personalized recommender systems for both patients and the doctors. There are apps for recommending hospitals, doctors, or even treatments based upon a vast healthcare database [28–30]. An example of one such recommender system in health domain is Practo. It is a full-fledged health app that has features such as getting doctors' appointments, ordering medicines online, online consultation along-with getting health-related tips, and managing health records [31]. Apps like Glow, TalkSpace, ZocDoc, or FindMyDoc are also based on the same idea [32]. Similarly, the scope of IoT in healthcare is also quite promising. Be it real-time monitoring of patient, tracking doctors in real-time, remote medical-assistance, tracking biomedical devices, or patient information management, a lot has been made possible using IoT devices [33–35].

3.4. Entertainment. When it comes to entertainment, many recommender systems have been developed till date. YouTube, Netflix, Hulu, Jester, Pandora, and TiVo are some of the most popular recommender systems in the field of entertainment. Personalized recommendations for each viewer based on his interests are what makes YouTube popular among the masses [36–38]. Similar is the case with Netflix, although it is the most popular recommender system because of the Netflix prize contest introduced in 2006 [39, 40]. It is an online video streaming site that recommends movies and TV shows to the viewers based on their interest, most popular items, and item-to item similarity [41, 42]. In case of IoT, smart devices like Google Home, Amazon Echo, Amazon Firestick, and Alexa are the sources of entertainment along with the feature of smart-home facilities [43].

3.5. Social Networking Sites. Facebook, Twitter, LinkedIn, and MySpace are the most popular recommender systems used for social networking. These sites help the users make new friends; communicate with them; share pictures, videos, or voice notes; or tag them [44, 45]. Adding friends, people you may know, pages you may like, and jobs you might be interested in are some of the features provided by these social networking sites. Similarly, Twitter is a social network platform that allows its users to share a short message called a tweet, with their followers, follow people, tag people in their tweets, and retweet [46, 47]. A similar kind of work has been done using IoT. Social Internet of Things (SIoT) and Social Internet of Vehicles (SIoV) are the examples. These two concepts are based on establishing social relationships among objects, forming a social network where the participants are intelligent objects or vehicles [48–50]. Various platforms for the development of both IoT and recommender systems are given in Table 2 along with the most popular products of both.

The next section is focused on the need for collaborating both IoT and recommender systems and how these two different research areas can be benefitted from each other giving the best of both worlds.

4. Need for Collaboration

Recommender systems focus on providing recommendations to the users based on their likes, dislikes, or how they interact with a given system [4, 5]. The primary goal for the same is "Providing right recommendations to the right user at the right time" [51]. But how often is that often? Take any E-commerce site for instance. While browsing for an item a user might want to purchase, he/she may get recommendations at the bottom of the site for things he/she purchased in the past. Now, imagine being recommended something you already have, while you are looking for something which is not even remotely related to what you are being recommended. Would you call that E-commerce site intelligent? Of course not. Take another example, while using some apps on your smart devices, you get ads popping up on either the top or bottom of your screen for some other apps. This is something which the user has not even asked for. Of course recommendations are required at times to make things convenient but getting them when the user is probably not even looking for any sort of recommendations and he knows exactly what he wants and from where that tiny pop-up on the screen can be pretty much annoying; and hence, this directly impacts the usage of that site by the users. So what we as the end-users require is valid

Table 2: Toolkit and popular products.

IoT	Recommender Systems
Platform / Toolkit for Development	
Amazon Web Services	Azure Machine Learning Studio
Google Cloud IoT	R Studio
Microsoft Azure IoT Suite	Rapid Miner Studio
SAP	Apache Mahout
Salesforce IoT	MATLAB Toolkit
Oracle Internet of Things	SAP HANA
Cisco IoT Cloud Connect	Lenskit, LibRec (Java)
Bosch IoT Suite	CoFE
IBM Watson Internet of Things	Scikit, Crab, GraphLab (Python)
ThingWorx IoT Platform	TensorFlow
Popular products/ applications developed	
Amazon Echo, Google Home	Netflix
Kuri	YouTube
Aladin	Spotify
Cloud Your Car	Pandora
RoboVac 11	Last.fm
ProGlove's Smart Glove	MyStrands
Kohler Verdara Smart Mirror	LinkedIn
Canary Smart security system	Amazon
OMNI Smart Cycling helmet	Hulu
MyMD Band	Practo

recommendations at the valid time based on our needs and not always based on our past. Two main reasons for the same can be the following: (1) interests tend to change with time, and (2) if a user has already purchased a certain item, he/she may not be looking for it the very next time he/she visits that site. Figure 1 gives an overview of the general recommendation framework.

IoT or Internet of Things is an umbrella term that basically covers and connects objects and knowledge using the Internet [52, 53]. Researchers have been exploring the potential uses of IoT since the day the term was introduced by Kevin Ashton in 2009 [54]. The concept of smart cities, smart homes, smart transport, smart hospitals, and anything else with the prefix "smart" for that matter has proven to be nothing but a boon of IoT since its introduction [55, 56]. From having RFID chips to sensor-based systems, a lot of work has already been done in this area [57, 58]. However, there are some research challenges and possibilities that still need to be worked on [3, 59]. We can combine IoT with another research area to see how well it performs and what possible benefits it can bring to that area.

For example, there is a movie recommender system that suggests and plays movies for the user based on his likes and previous view history. Suppose this user is a fan of thriller and action movies. Now one fine day, the user is feeling low and missing his childhood days. He opens his system and logs into the movie recommender system, where again he is being suggested to watch the new series of The Dark Series or Die Hard, but since he is low, he does not want to watch either and tries to find something else to cheer himself up. Now imagine if this movie recommender system would take users' feelings and emotional state into consideration and then make the recommendations. Rewind back, the user is feeling low, he logs into the system, the system senses his emotional state and, instead of recommending him his regular movies, suggests him movies to cheer him up like Home Alone or Baby's Day Out. Recommender system alone could have not been much efficient in this scenario, but recommender systems combined with IoT did wonders (hypothetically). Therefore, based on this example, we can pretty much imagine how easier our lives would be when we would combine both IoT and recommender systems to get the best of both worlds. Figure 2 depicts a combined framework of both IoT and recommender systems.

5. Use Case Scenarios

In this section, different use cases are discussed to see how a recommender system behaves with and without IoT integration, respectively. Consider Netflix. It is a hybrid recommender system based on collaborative and content-based filtering. For every new user who creates a Netflix account, a common homepage is displayed wherein the options for movies and TV series are based on how popular those items are among the other Netflix users (collaborative filtering). Now, once a user starts using Netflix, he or she views some content, and based on his or her viewed content, the homepage gets modified accordingly, i.e. the suggestions given at the home page are the ones like the type of content they have viewed previously (content-based filtering). Although Netflix is one of the most popular recommender systems, but it has one drawback which is lack of serendipity. Once a user starts to use Netflix, every time he logs into their account, they are recommended content which is either like the content they have viewed previously or the content which is popular among the users who are like them. Therefore, the problem of overspecialization arises; i.e., they are recommended only one kind of content and the system therefore lacks serendipity. The general working of Netflix recommender system is considered for the use case, as depicted in Figure 3.

Now, consider the use case of RecIoT as given in Figure 4. The recommendations generated here are not solely based on the user and content similarity; rather the emotional state of the user is also taken into consideration. Every time a user logs into his account, his emotional state is observed and based on that the recommendations are generated. Smartphones these days are not just limited to calling and texting; rather they are capable of much more than that. One of such features is that of measuring stress level of a user, as provided by Samsung smart phones. All a user must do is keep his thumb on the touch sensor; and in a friction of seconds, the stress level is calculated in terms of highly stressed, stressed, medium stressed, low stressed, and no stress. Another possible functionality is capturing user facial features via webcam or the smartphone camera to predict his emotional state. These functionalities can be combined with

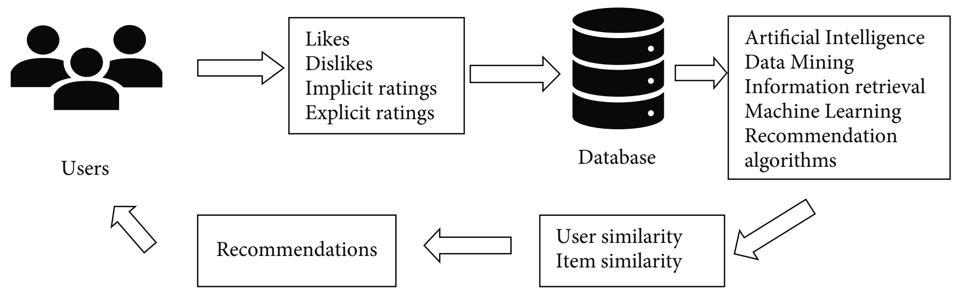

Figure 1: Recommendation framework.

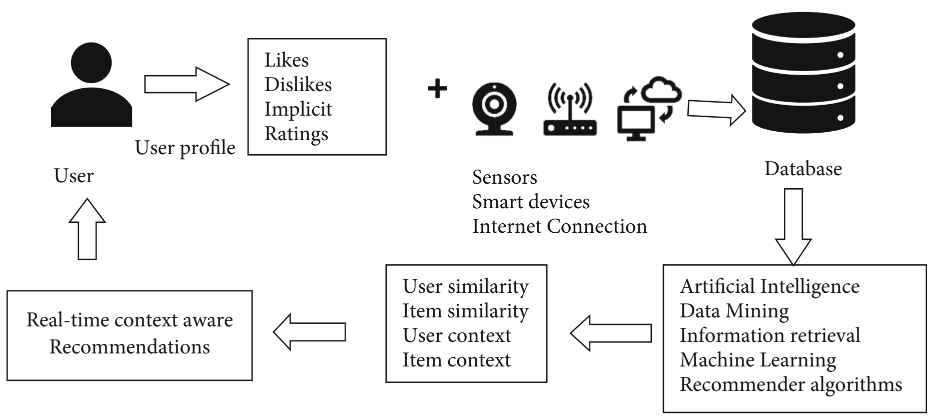

Figure 2: Framework of IoT-based recommendation.

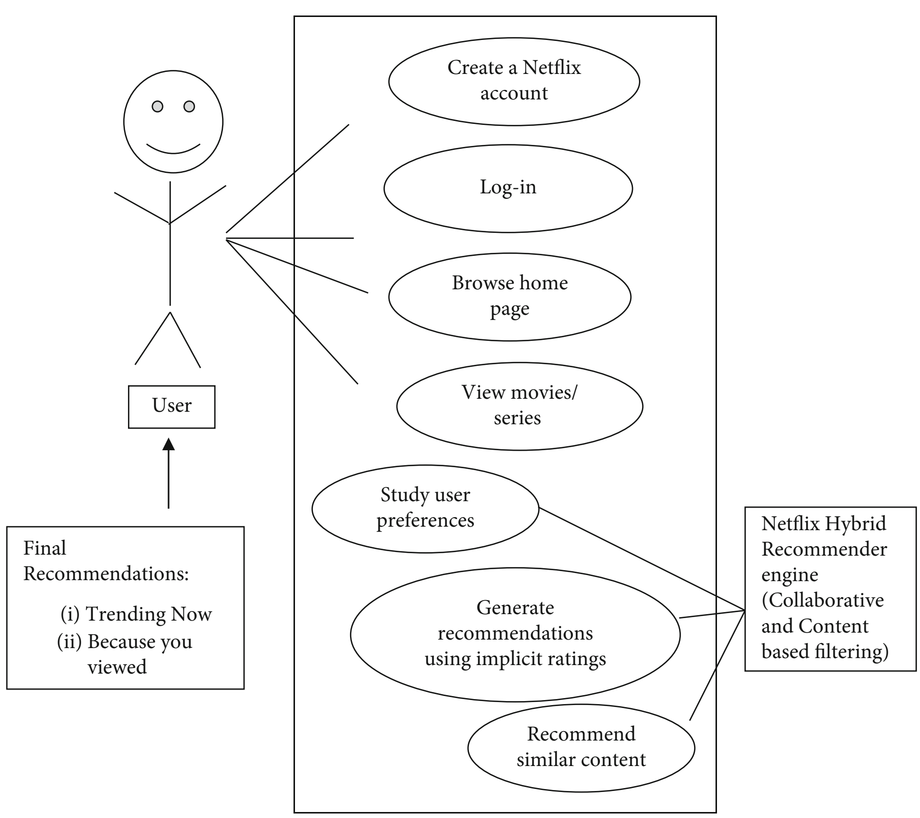

Figure 3: Use case diagram of Netflix recommender system.

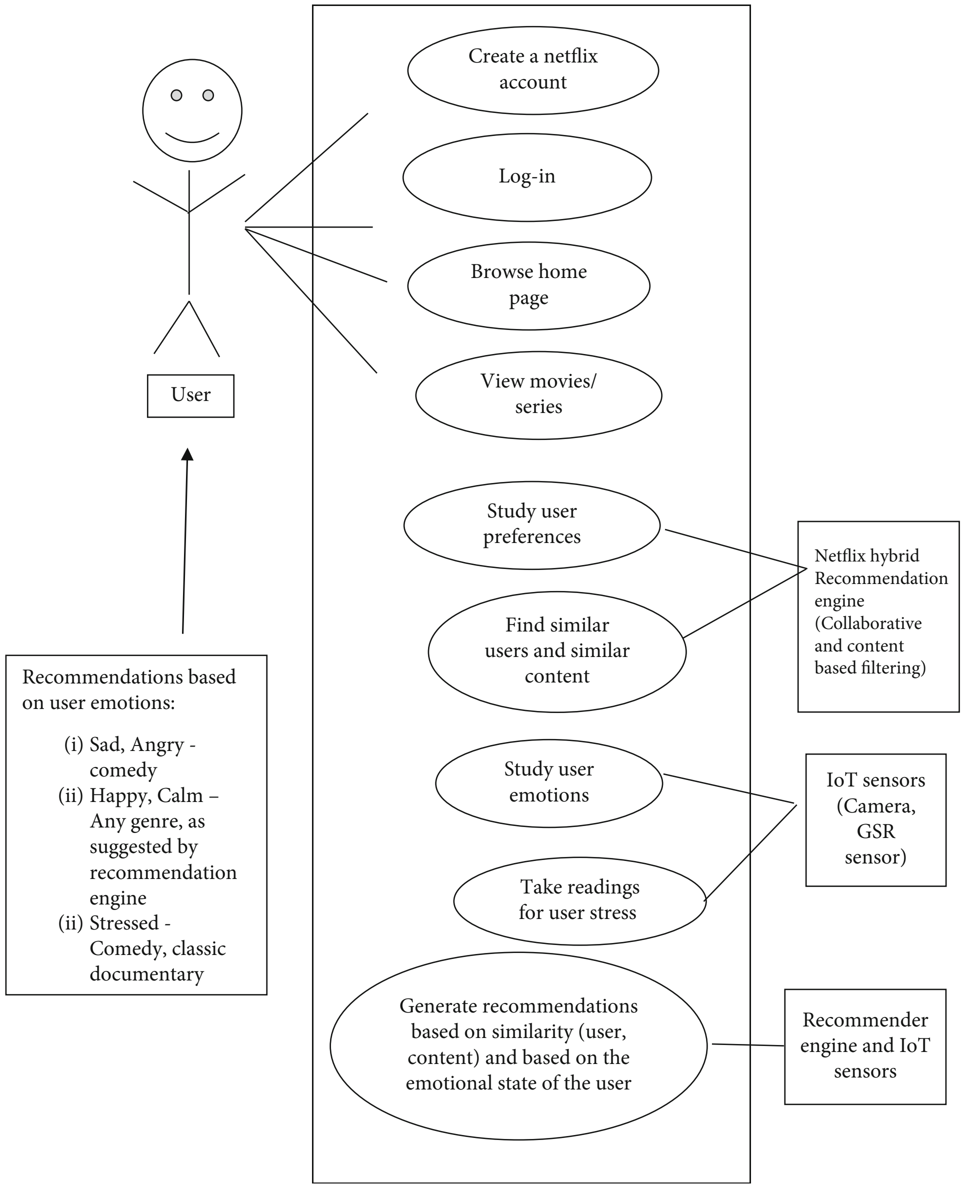

Figure 4: Use case diagram of Netflix RecIoT.

Netflix to provide more relevant recommendations which are directly related to how a user is feeling.

Figure 3 depicts how Netflix normally works, considering user and content similarity to generate recommendations, while Figure 4 proposes how Netflix would work when combined with sensors and cameras. The recommendations in the latter case are based on the emotional state and stress level of a user along with the content and user similarity. Table 3 gives a comparison of both the use-cases of Netflix with and without IoT.

6. IoT and Recommender Systems

In this section, the work that has been done so far towards collaborating the two different domains and the ongoing research is discussed. The work done is described categorically in the fields of smart education, smart healthcare, smart transport, and several other services that have been provided.

6.1. Smart Education. Smart education is nothing but making the learning process easier and more interesting for the students using IoT devices. The main purpose of introducing IoT in schools and colleges is to enhance level of personalization in higher studies. A general system for a smart education consists of learning resources, campus facilities, students, and faculty, all connected over the Wi-Fi. The researchers are continuously working towards interactive and personalized learning systems for improved education systems. One of the most prominent objectives of researchers towards improvement of learning system is to be able to generate recommendations based on the physiological state of the learner, instead of gathering that information explicitly. Technology-Enhanced Learning (TEL) is

Table 3: Comparison of Netflix recommender system with and without IoT.

	Without IoT	With IoT
Parameters considered	View history Browsing pattern User similarity Content similarity	View history Browsing pattern User similarity Content similarity Emotional state Stress level
Recommendation algorithm	Yes	Yes
Sensors	No	Yes
Webcam	No	Yes
Advantage	Hybrid recommendation engine	Serendipity
Drawback	Overspecialization	—

known to have focus on this very objective where context-based personalized recommendations are generated for a learner [60]. The authors have worked towards a similar goal of analyzing the effectiveness of recommendations generated using Arduino along with corresponding sensors and actuators [61]. Stress in an individual can be predicted or measured using inconspicuous, wearable sensors [62]. Wearable sensors act as personalized emotion management biofeedback systems capable of early stress detection and manipulating physiological state of the user as well [63]. Based on these works, the authors of the paper have described the open platform, named AICARP v2 that can detect variations in physiological signal learner [64]. If any variation is observed in the physiological signals of a learner in any stressful situation, he is recommended to relax and focus on sensorial activities like light, sound or breathing rate. Therefore, the recommended action can be professed by the leaner without interrupting the learning activity. For this study, learners preparing for the oral exam of their second language are considered.

A similar work based on TORMES elicitation methodology is presented by the authors in [65] to study the potential of ambient intelligence for generating more interactive recommendations in an emotionally stimulating scenario. Arduino platform is deployed to detect any variation in the emotional state of a learner and make interactive recommendations using diverse sensory communication channels like sound, vision, or touch. The other most important parameter to be considered for improved state of learning despite context-based recommendations is personalized recommendation. A learner must be able to learn anywhere at any time and access any knowledge resource as and when required. This concept is referred as ubiquitous learning that is aimed at improving the learning experience of any learner in any environment [66]. Student profile is not the only thing that needs to be taken into consideration while offering personalized recommendations to them. Contextual aspects should also be considered. Therefore, recommendations are generated by experts for the subject that a student intends to learn by taking their own past experiences with other students into consideration [67]. Keeping in mind the need for developing smart learning environment, the University of Jaen developed a SmartLab called UJAmI based on ambient intelligence to provide an assistive learning environment [68].

6.2. Smart Healthcare. Smart healthcare consists of two concepts: e-health and m-health services, for improving the quality of healthcare using smart devices in smart environments. The intelligence of recommender systems and the real-time observations taken by IoT devices has paved the way for research in the field of healthcare aiming towards gathering context-aware information of a patient and acting upon it accordingly. The concept of smart health is introduced to improve the quality of healthcare system in a smart city using the concept of recommender systems [69]. Recommendations for routes, means of commute, or required physical activities are generated for the citizens based on their real-time health conditions and preferences. Similarly, personalized healthcare facilities can also be attained using IoT and ambient intelligence in smart homes. Continuous monitoring of factors like heart rate, breathing rate, electrodermal activity, and body temperature using wearable noninvasive sensors is of utmost importance for developing any smart healthcare system [70]. These factors are considered for developing an automated smart healthcare environment that automatically adjusts the room temperature when a person is down with fever or control other home automation devices based on the data gathered by the sensors [71].

This research is not limited to healthcare facilities in smart homes only, but the researchers have focused on the health of the users while travelling as well. ProTrip RS is a travel recommender system that generates personalized recommendations based on the travel pattern, actions, and demographic information of the user [72]. ProTrip acts as a health-centric RS that suggests the food availability to users based on their personal choice and nutritive value. The major beneficiaries of ProTrip are the travelers with long-term diseases and people following strict diet plan. A similar work is conducted by Jose Antonio et al. targeting the problem of Allergic rhinitis. The authors introduced AllergyLESS, a recommendation system for the citizens suggesting them the walking routes with minimum exposure time to allergens [73]. The quality of air and presence of allergens is measured using wireless pollution posts and open-data sources. Another work focusing on smart health is CUIDATS, an IoT-based hybrid health monitoring system integrating both RFID and WSN technologies into a single platform to track the status and location of patients as well as other medical assets [74].

Similarly, Yong et al. introduced an IoT-based fitness system to track and monitor the health statuses of users of a gym [75]. While exercising, the data of the burnt calories and heart rate is gathered by sensors and fitness band. Afterward, this data is sent to the system to be analyzed using CNN, and based on the results, further exercises or activities are recommended to the user. The system further considers image recognition along with activity recognition for more reliable results. However, lack of standard datasets to train an efficient model poses a huge research challenge. Further, Yang et al. presented an intelligent health recommender system emHealth, for patients suffering from depression or emotional disorder towards retrieving personalized therapies in the shortage of medical resources [76]. Further, a personalized mobile phone app is developed to collect emotional data of volunteers using a Self-rating Depression Scale. Based on the factors that lead to depression and the level of depression, personalized recommendations are given to the user in terms of treatment solutions and emotional improvement suggestions. Similarly, novel recommendation methods in the IoT enabled m-health field following the principle of Quantified-Self are proposed, to recommend healthcare devices, mobile apps, and physical movement plans for the patients using the concept of virtual coach and virtual nurse [77]. Following the same direction, Jabeen et al. proposed an IoT-based efficient hybrid recommender system for detecting cardiovascular diseases using wireless sensor networks and provide personalized recommendations based on a patient's age, gender, and clinical test results [78]. However, the proposed model is yet to be implemented.

6.3. Smart Transport. A system that can sense the traffic, finding the shortest route, sensing the condition of the road, or finding vacant parking space is what comes to our mind on hearing the word Smart transport. Live tracking of vehicles using GPS, using google maps to reach any destination or accessing any information over the Internet, has made the lives of vehicle drivers somewhat convenient. However, there is one major issue which has still not been payed much attention to, yet is very troublesome for any driver, i.e., finding a parking slot [79]. Taking this problem into consideration, a Mobility Recommender System has been proposed in [80] with the prime focus on a car-based multimodality. The objective of the system is to promote the use of public transport. Any user may start the journey from home in personal vehicle, but once he finds a suitable parking slot in any parking area linked to a public transport, he may park his vehicle there itself and use public transport to reach the destination. Another work focusing on public transport is Urban Bus Navigator, an IoT-enabled navigation system that provides micronavigation and crowd-aware route recommendation services to the users [81]. Micronavigation is a flimsy contextual guidance of riders along a bus journey by identifying the boarded bus vehicles and tracking the progress of journey, while crowd-aware route recommendation focuses on suggesting less crowded and better routes to the bus riders by collecting and predicting the level of crowd on bus journey.

Finding a parking space without the need for driving here and there is still seen as a research challenge, although there exist a few mobile parking applications that help the driver locate to an available parking slot. One of such applications capable of recommending a vacant parking space to the driver, based on the context as well as user preferences, is proposed in [82]. Another similar work is introduced by Win and Srisura. The authors proposed a constraint-based recommendation approach to help car owners find their parking lots using mobile application [83]. Similarly, a novel cloud-based smart vehicle parking system based on VANETS has been proposed in [84]. The system delivers information about an appropriate vacant parking space to the user and recommended parking slots along with booking options. The recommendations generated are based on factors like drive time, distance to the parking slot, parking fee, walking distance from the parking slot to the destination, and traffic congestion. Another concept in the field of smart transport that is gaining popularity these days is Vehicular Social network or Social Internet of vehicles. A novel system that considers vehicles as recommenders by creating a social network of vehicles based on fog and cloud computing is proposed in [85]. Another context-based smart parking lot recommender system is proposed for smart cities [86] that considers user context along with parking information while generating the recommendations. The system takes into consideration each driver's context including his preferences, driving experience, location of the vehicle, the vehicle's properties, and other parking information.

6.4. Other Services. Services like smart shopping assistance, finding the nearest stores, gas stations, restaurants, and smart homes are the other areas which have been benefitted by collaborating IoT with recommender systems. Using IoT in the existing systems has led to generation of proactive recommendations, where the system automatically generates recommendations for the user upon detecting the requirement. A design for the same is proposed in [87], where a context aware recommender system generates recommendations for gas stations, restaurants, and places of attraction, proactively using the concept of IoT. Moreover, with the rapid development of IoT-based systems, there is a growing need for recommending more IoT services to a user based on the smart devices he owns. For that purpose, a graph-based service recommender system is proposed for IoT services recommendation [88]. Similarly, a real-time data-based personalized recommender system named WayGoo is introduced for event management tasks [89]. The objective of the system is to enhance user experience while visiting a museum or while attending any conferences or a function using personalized recommendations about the events.

The primary objective of any product or application is to achieve customer satisfaction. The sole purpose of creating a customer-oriented environment is to enhance user experience, both online and offline. However, this often becomes an issue in offline stores due to lack of professional assistance, long queues at the billing counter, out-of-stock products and figuring out which product is more popular, unlike online stores where user browsing pattern is used to figure

Table 4: Comparative study of literature.

System	Parameters considered	Recommender algorithm	IoT device	Research gaps
[30]	User health data User location	Composite service planner algorithm User preference algorithm	Wearables Body area network Body sensor network	Only prototype model developed
[60]	User location Time	Context-aware	—	Capturing and use of contextual data
[64]	User physiological data	Context-aware	Arduino Sensors Actuators	Translation of physiological to effective states Conjunction of IoT sensors with RS in educational scenarios No real-time implementation
[71]	User health	Semantic reasoning	Wearable sensors Home automation devices	Performance evaluation of proactive monitoring
[72]	User demographics Travel sequence	Ontological knowledge-based filtering	Wearable sensors Smartphones	Integration with social media Development of mobile application Gathering feedback from current users
[75]	Calories Heart rate	CNN SVD	Sensors Smart phones	Small dataset Not yet evaluated
[76]	Emotional disease	SVM Decision tree	Smart phones	Dataset does not relate to ground-truth values, and the recommendations are solely based on theories
[77]	Patient data	Nearest neighbor	Wearables	A future work is intended towards implementing the system. Further, authors plan to detect anomalies in the proposed system and send added suggestions to users/physicians
[78]	Customer interest	Nearest neighbor	—	The proposed system is so far evaluated for movie recommendation and compared with existing approaches and is yet to be implemented in E-commerce
[79]	Available parking slots Arrival time	Co-relation coefficient	GPS Smartphones	Design of an algorithm to determine the exact vacant slot
[81]	Boarded buses Crowd	Personalized recommendations	Smartphones Wi-Fi-enabled buses	Long-tail problem in terms of calculating exact number of passengers
[84]	Drive time Parking fee Distance to parking facility	Contextual recommendations	VANETs Parking side units Roadside units	Privacy and security issues
[86]	Driver info Parking info	Context-based model	Parking sensors	Synthetic dataset
[89]	Event information User location & preferences	Naïve Bayes	Smartphones GIS server	Cold-start problem
[90]	Customer shopping behavior & preferences	Fuzzy screening	RFID	Restricted to intraorganizational supply chains Considers only two apparels for collocation
[92]	Use-user relation User-thing relation Thing-thing relation	Probabilistic matrix factorization	RFID tags Sensors	Does not consider the dynamic attributes of the objects
[93]	Social relationships between people and things	—	RFID, sensors, Arduino	No proof of concept, lack of interoperability among IoT devices, not implemented.
[94]	User behavior Home appliances	Kalman filter model (hybrid)	Sensors	High cost of deployment
[14]	User location Weather conditions	Hidden Markov model	Sensors	Scalability

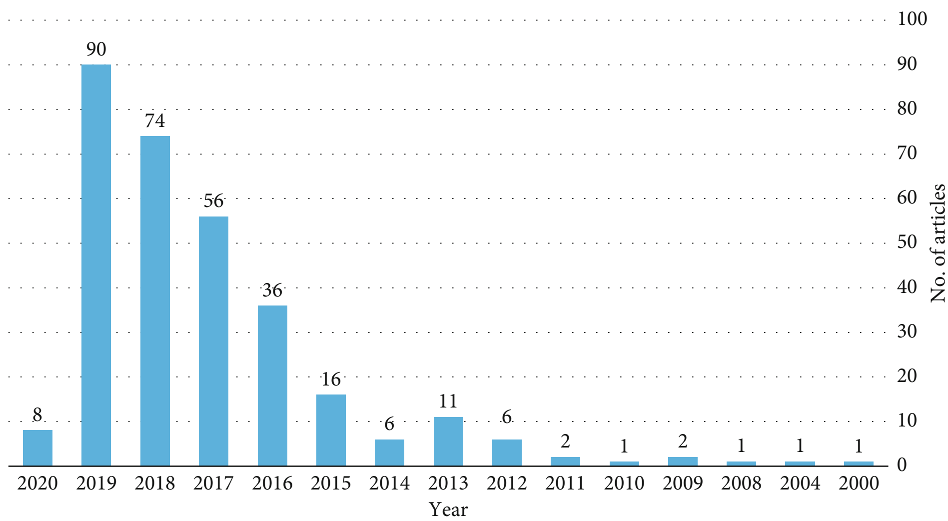

Figure 5: Documents per year as per Scopus database fetched on January 8, 2020.

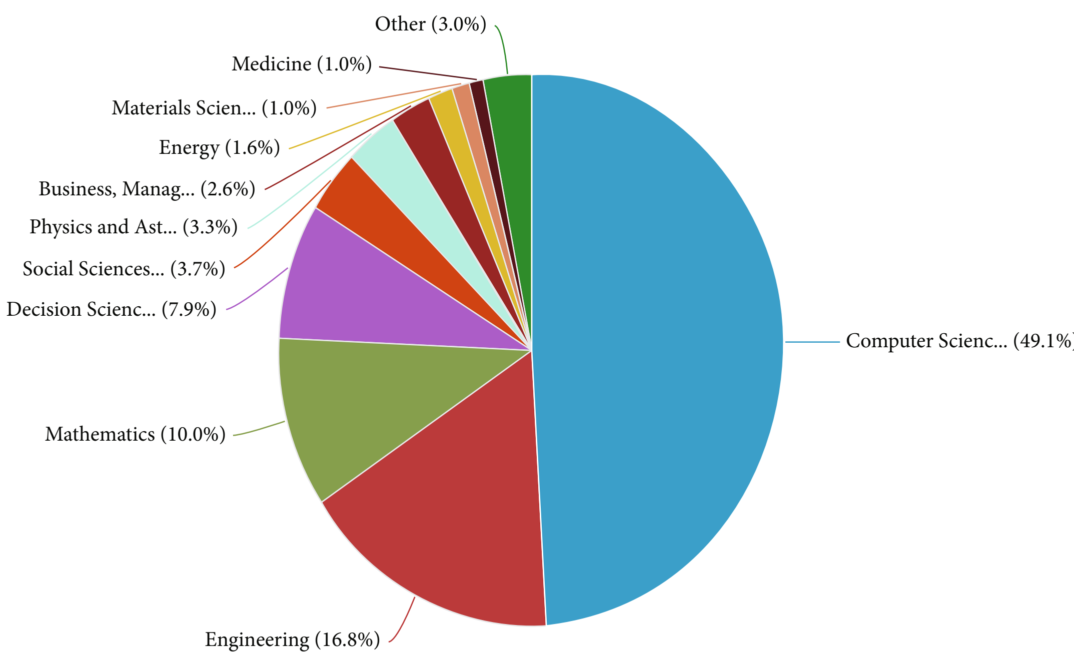

Figure 6: Subject vise documents as per Scopus database fetched on January 8, 2020.

out the same. Therefore, an item-level RFID-enabled merchandizing store management system is proposed in [90] to provide customers with product information and to promote sales during shopping. Customer behavior and preferences are captured using RFID devices for proactive marketing on individual level. A similar work is conducted in [91] to mine customer preferences based on their behavior and shopping pattern in physical stores. In another work, a probabilistic matrix factorization-based framework is proposed towards the thing's recommendation in IoT environment [92]. Information from users' social networks and things' correlation networks is integrated to obtain heterogeneous data of user-user relations, thing-thing relations, and user-thing relation. Although the system copes up with the cold-start problem, however, it still does not take the dynamic attributes of things into consideration.

Similarly, Saleem et al. proposed a novel concept for the exploitation of the social IoT for recommending services amid various IoT applications [93]. The basic assumption of this study is that things or objects form a social circle when interacting with multiple users or objects. The authors further described the implementation challenges for the proposed system, in terms of lack of interoperability among several IoT devices, social network management, trust, privacy, security, network navigability, and lack of proof-of-concept. Further, Chen et al. proposed a weighted hybrid model based on the Kalman filter model to forecast what users might wish to do next, when positioned in a smart home

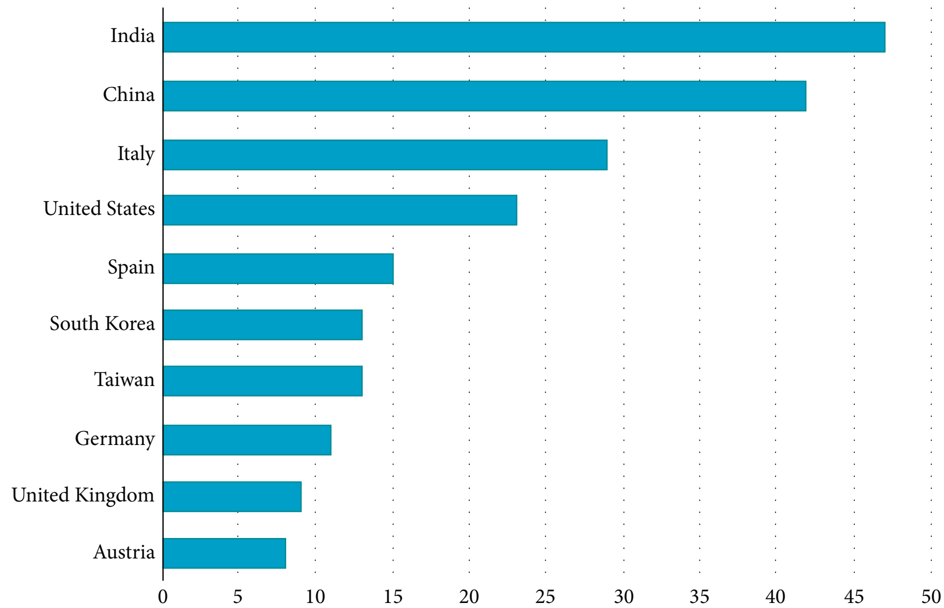

Figure 7: Country wise documents as per Scopus database fetched on January 8, 2020.

environment [94]. User activities are recognized as the operation of smart devices, such as opening or closing the door, turning up, or turning down the air conditioners. Empirical results confirm that the hybrid model can be used to heighten the distribution of weights of each component and attain more rational recall and precision values. However, the cost of deployment is quite high since multiple sensors need to be installed to receive user context.

Following the same work, Chakraverty and Mithal proposed a weather and location-aware recommender system operating in a real-time environment [14]. It considers weather data acquired by IoT sensors to provide recommendations to the users inhabiting that geographical locality. Based on the historical sales trends under comparable weather conditions, recommendations for holiday destinations, products, and stocks are made. However, the system suffers from scalability problem. A comparison of existing systems based on both the approaches is described in Table 4. Researchers are also working on applications of smart cities which use recommender systems [95–98].

7. Current Research Trends

This section suggests the amount of work that has been conducted till date in IoT-based recommender systems. The criteria for analysis of the data are year of publication, subject area, and country the research is conducted in. For this analysis, Scopus dataset has been referred and the data is as per the statistics on January 8, 2020.

Based on Figure 5, it can be observed that the work on RecIoT gained recognition from 2013 onwards and henceforth increased gradually. The concerned domain soon started grabbing the attention of researchers worldwide and became popular by the year 2019, resulting in 90 research articles. For the year 2020, 8 research articles have already been added to the Scopus database, indicating towards a drastic increase in the number of research articles.

Figure 6 suggests the subject-vise distribution of the research conducted on RecIoT. It can be observed that almost half of the work (49%) has been conducted in Computer Science domain with engineering area (16%) next in line. Only 1% of the articles focus on medicine, material science, and energy, indicating the vast scope of future research.

Figure 7 indicates the country-wise statistical analysis of the research. It can be clearly observed that India (47) is leading this particular research domain followed by its neighbor China (42). Italy (29) and United States (23) follow next. Further, countries like UK (9), Austria (8), and Greece (8) have comparatively contributed less.

Based on these statistics, it can be concluded that RecIoT is still a young research domain and can be explored further. There may lie some aspects of RecIoT which are yet to be unveiled. Further, since very little research has been conducted in Medicine and Material sciences, researchers may work in these application domains. RecIoT assures context-based recommendations and hence holds a promising future towards providing better services to the user. Therefore, further research needs to be conducted on RecIoT.

8. Conclusion and Future Scope

Over the past two decades, Internet of Things (IoT) and recommender systems have gained a lot of popularity in both the research and the industrial sectors: reasons being multifold, ranging from the ability to connect several devices at the same time, sharing data over the Internet, providing services to the user based on real-time requirements, to intelligent decision-making. Both the research areas are equally beneficial in their respective domains. However, combining them both has a more promising future in terms of providing better services in multiple application areas, be it smart education, smart transport, or smart healthcare. Although researchers have started working towards integrating both IoT and recommender systems, yet we are still on the very initial stage and only a few application areas have been targeted so far.

This article is focused on a detailed review of the work that has been done so far towards combining both IoT and recommender systems. The use-case of Netflix has been discussed to see how the current system generates recommendations based on user and content similarity. Further, another use-case of Netflix when combined with IoT devices has been described to see how recommendations could be generated considering multiple factors, supposedly emotions as described in Figure 4. A categorical study of the state-of-the art of IoT-based recommender systems is discussed along with the ongoing research in the fields of smart education, smart healthcare, smart transport, and other services.

Based on the review conducted in this paper, following research gaps were found: (1) there is a lack of datasets for IoT-based recommender systems which makes evaluation a bit difficult, (2) the existing algorithms in both IoT and recommender systems are not effectively scalable for surplus volume of data, (3) traditional context-based systems are limited to 2 or 3 dimensions only, and (4) very few works have deployed hybrid model for IoT-based recommender systems till date, to the best of our knowledge.

In the future, we are planning to work towards the above-mentioned gaps. Further, recommender systems have some other limitations also, namely, cold-start problem, gray-sheep users, and overspecialization. We believe that developing an IoT-based hybrid-recommendation model will overcome these limitations. Therefore, we aim towards developing a hybrid real-time based recommendation model to further explore the possible benefits of IoT in existing recommender systems. The primary focus is to provide relevant and better recommendations using IoT concept, aiming towards the improvement in the cold-start problem, serendipity problem, and in-depth study of the gray sheep users.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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