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A New Approach to Recommender Conceptual Architecture in Learning Internet of Mobile Things

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Abstract

Mobile Internet of Things (MIoT), one of the important sub-fields of the Internet of Things (IoT), faces several challenges, including mobility, dynamic environmental changes, resource constraints, and real-time data processing. Predictive learning, as a powerful approach to data analysis and prediction of future events, can play an important role in improving the performance of MIoT systems. This paper comprehensively reviews predictive learning in the MIoT field and examines the challenges and research opportunities. The expansion of IoT systems has attracted significant attention from the research community. It has brought many innovations to smart cities, primarily through the Internet of Mobile Things (IoMT). The dynamic geographic distribution of IoMT devices allows devices to sense themselves and their surroundings at multiple spatiotemporal scales, interact with each other over a large geographic area, and perform automated analytical tasks anywhere and anytime. Most geographic applications of IoMT systems are currently developed for anomaly detection and monitoring. However, shortly, optimization and prediction tasks are expected to have a greater impact on how citizens interact with smart cities. This paper reviews the state of the art of IoMT systems and discusses their critical role in supporting predictive learning. Predictive learning in MIoT leverages various machine learning and artificial intelligence methods. These methods fall into two broad categories: Supervised learning and unsupervised learning. In addition, more advanced hybrid methods such as deep learning and reinforcement learning are also being used in this area.

The maximum potential of IoMT systems in future smart cities can be fully exploited in active decision-making and decision delivery through a predictive action/feedback loop. We also examine the challenges and opportunities of predictive learning for IoMT systems in contrast to Geographic Information System (GIS). The overview presented in this paper highlights guidelines and policies for future research on this emerging topic.

Keywords: Internet of things, Predictive learning, Smart cities.

1 | Introduction

The Mobile Internet of Things (MIoT) refers to systems in which mobile objects (Such as cars, robots, wearable devices, etc.) are connected to the Internet of Things (IoT) network and collect, process, and exchange data. Due to their mobile nature, these systems face unique challenges that require innovative solutions for management and optimization. Predictive learning, an advanced machine learning technique, and artificial intelligence can predict future events by analyzing historical and current data. This capability can

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help MIoT systems operate more intelligently and optimize their resources. The IoT has received significant attention from the research community since it was first introduced by [1]–[3]. The basic concept of the IoT is that every physical object in a smart city is interconnected and can act as a sensor embedded in small computers, which are then geographically distributed over a large area of a smart city. An IoT device is always connected via a communication network, ranging from short-range networks (e.g., Bluetooth, Zigbee, Near-Field Communication (NFC)) to medium-range networks (e.g., Wi-Fi, Digi Mesh) to large-range networks (e.g., LoRaWan, cellular, WiMax). Today, IoT devices are typically expected to collect sensor data, communicate with each other, and make decisions without human intervention [4]–[7]. Some examples of IoT devices include smart traffic lights, smart parking meters, smart home meters, smartphones, and wearable devices [8]–[13]. The IoT market in smart cities has not yet truly matured due to several technical, political, and financial barriers. However, previous survey papers have shown different perspectives regarding the role of IoT in smart cities. These are mainly related to IoT architecture concerns such as IoT elements, features, protocols, and standards [14]–[18], as well as the development of new IoT applications such as smart factories [19], smart homes [20], and smart hospitals [21].

The Internet of Mobile Things (IoMT) takes this further and can be defined as "the extension of the IoT concept to mobile devices, which is essentially any IoT device that moves.” Rather than having a fixed location in a smart city, an IoMT device can be anything people wear or carry, such as clothing, smartphones, and wearables. Or things used for transportation, such as cars, trucks, trains, bicycles, and airplanes. When these IoMT devices are connected, they can sense themselves (e.g., speed, acceleration, and direction) and their surroundings (e.g., temperature, sound, and air pollution) and exploit available resources by edge, fog, and cloud computing.

Therefore, IoMT devices generate unlimited data streams from many indoor and outdoor locations, which require a low-latency database to store and explore data in space. Time is important because different time windows for managing IoMT data streams affect preprocessing, analytical, and visualization tasks. Some examples include index windows [22], sliding windows [23], wet widows [24], and skewed windows [25]. Different time windows have been proposed to deal with the transmission of data streams where the data rate can overwhelm the processing power of computational resources at the edge, fog, and cloud. In contrast, the spatial dimension has been neglected so far despite data streams generated by IoMT devices moving across large geographic areas with fine spatial granularity. There is now a growing interest and demand for developing IoT-Geographic Information System (GIS) platforms that can manage data streams generated by IoMT devices. This paper is a step in this direction because IoMT paves the way for predictive learning.

As shown in [26], predictive learning is a term that is often misused. Rosen defined it as "a system whose current state is determined by a (Predicted) future state." At the same time, Nadin [27], [28] defined it as "a system whose current state is determined not only by a past state but also by possible future states". However, both authors agree that prediction and prediction are not interchangeable concepts. The agreement is that a predictive system makes decisions to influence the future to benefit the user. Meanwhile, a predictive system uses a predictive model that can predict the system’s future state.

This paper defines predictive learning for IoMT as a system in which the current state is determined by the past and future behavior of IoMT devices, as represented by the dynamic geographical distribution of IoMT devices over time. This is essential to build context intelligence into predictive learning models. This is mainly because IoMT devices are equipped with various sensors that produce data streams of spatiotemporal information to infer contextual intelligence about what is happening, where and why it is happening, and what should be done about it. In other words, contextual intelligence requires that predictive learning models have: 1) a context sensing strategy for relevant past events detected or monitored by IoMT devices, 2) spatiotemporal awareness of current context variables continuously applied to the collected IoMT data, and 3) user-centered awareness of the preferred future so that the system can influence and help the user make appropriate decisions.

Edge-fog-cloud computing is the current technology that allows us to run machine learning algorithms and build predictive models. In contrast, our current GIS technology was developed primarily to support predictive systems. Recent efforts in designing IoMT-GIS have highlighted the fundamental limitations of GIS in processing IoMT data streams. Adding the capabilities of a predictive learning model to GIS only creates further barriers to using GIS to run machine learning flows to build predictive learning models.

Since a relatively systematic overview of IoT systems has recently been published elsewhere, our paper focuses on IoMT systems. Our goal is not only to provide an overview of IoMT research related to each stage of a predictive learning model but also to provide some guidelines and future research directions for building predictive learning models for IoMT systems.

The rest of the paper is organized as follows. Section 2 introduces the main concepts of IoMT systems and compares the data collection strategies currently used in research projects. Section 3 describes the main steps in building predictive models for IoMT systems. Section 4 describes the research conducted on context sensing at the network's edge, while Section 5 introduces context intelligence using fog computing. Section 6 describes prediction and intelligent actions for predictive learning. Section 7 overviews the challenges and opportunities for building predictive learning for IoMT systems. Finally, conclusions and future research are given in Section 8.

2|Mobile Internet of Things

In general, IoMT devices are equipped with a variety of sensors, from accelerometers and gyroscopes to proximity, light, and ambient sensors, as well as microphones and cameras. They also have computing capabilities that allow them to use a wide range of communication interfaces, such as Wi-Fi, Bluetooth, or NFC. Understanding themselves and their surroundings is key to generating "streams of small data" in space and time in a way that shares many of the characteristics of big data, including the five Vs: Variety, velocity, volume, accuracy, and value.

The nature of IoMT data streams is multi-modal, diverse, heterogeneous, and voluminous. Often delivered at high velocity and with a degree of uncertainty. These data streams generally have distinctive characteristics that make traditional GIS storage, management, and processing obsolete. These characteristics can be described as one of the following:

I. Data in motion: IoMT devices can sense themselves using context variables such as speed, acceleration, and direction at a specific location and time. However, they can also feel their surroundings using context variables such as temperature, sound, and air pollution, and depending on the type of sensor deployed within the IoMT device; these variables may have different spatial ranges (e.g., from 1 and 10 meters to 100 meters and 1 kilometer) as well as temporal granularities (e.g., from milliseconds and seconds to hours and days). Context-sensing data constantly moves from IoMT devices to edge and fog nodes to the cloud, depending on the available processing power and storage resources.

II. Data in different forms: Depending on the context intelligence intended for a predictive learning model, each IoMT device can perform different sensing functions to collect time series and event data. This results in various data types, including structured, semi-structured, unstructured, and mixed data streams.

III. Data at rest: It is undisputable that IoMT devices generate large volumes of data streams that are always associated with a location over time. This poses a challenge to capture, process, and manage data at an appropriate spatiotemporal scale, which is required for a priori identification when developing predictive learning models.

IV. Questionable data: Uncertainty refers to biases, noise, and anomalies in the data stream caused by reasons such as data inconsistency and incompleteness, latency, ambiguity, deception, and approximation.

V. Q-Data of many values: The potential hidden in the depths of IoMT data streams is significant and has not yet been fully exploited. Processing, calculating, analyzing, and making decisions based on this context can help us support decision-making actions. This paper considers predictive computing a key approach to exploiting this potential.

Table 1 compares some selected research projects in which data from IoMT devices has been collected using sensors such as Global Positioning System (GPS), Radio Frequency Identification (RFID) tags, and cameras. They are categorized into four common types: structured, unstructured, semi-structured, and mixed. Structured data is information that conforms to formal data schemas and models. Meanwhile, unstructured data does not follow any predefined data model. Semi-structured data is not contained in a data model but has organizational structures that make it easier to analyze (e.g., CSV, XML, JSON files). Mixed data is a combination of different types of data together. It is argued that much of the IoMT data generated today is semi-structured or unstructured. A literature review of our selected projects confirms this hypothesis and also reveals the following major issues in GIS:

I. Uniqueness: IoMT data streams are a unique type of spatiotemporal data because they represent a massive cloud of location points over time in a way that current spatial representations (e.g., routes, time geography, and layers) cannot capture the volume of these data points and the semi-structured and unstructured data associated with them.

II. Propagation: We consider propagation a discrete-time process that starts from one data point to another, is capable of gathering context information, and is controlled by the rate of progression between two or more data points. Spatiotemporal progression matrices have been used in the past, but they cannot handle unstructured data streams. More research is needed in this area.

III. Batch processing: *Table 1* clearly shows that accumulated data streams can be entered and require processing at various speeds, from batch to near real-time or real-time processing. Most research projects have used batch processing to analyze their data. However, the development of GIS flow is needed to analyze the data streams as they arrive.

Table 1. Overview of internet of moving things (Internet of mobile things) research projects.

Data in Many Forms	Data at Rest	Goal	Sensors/IoMT Devices
Mixed	Batch	Moving Object Map Analytics (MOMA) for connected vehicles	GPS, camera, environmental sensors
		Location prediction	Global System for Mobile Communication (GSM) traces, cellular calls, survey data
	Real-time	Mobility-Aware Trustworthy Crowdsourcing (MATCS)	Crowdsourced data
		Urban trajectory data analytics system	GPS, rain gauge data, road incident report, social media
Semistructured	Real-time	Smart object framework	Sensors
		Traffic monitoring	Traffic lights
Structured	Batch	Clustering of lot devices	Unmanned Aerial Vehicle (UAV)
		CityPulse framework	Bus
		IoT-based smart parking	Ultrasonic
	Real-time	Analyzing people's activities	RFID tags

Table 1. Continued.

Data in Many Forms	Data at Rest	Goal	Sensors/IoMT Devices
Unstructured	Batch	Ambient intelligence with adaptive decisions	Internet packet
		Ambient intelligence with adaptive decisions	Internet packet
		Media-aware secunty	RFID tags, Internet Protocol Television (IPTV), Voice over Internet Protocol (VoIP), Video on Demand (VoD)
		Locationing phone	Wifi scanner, bluetooth scanner
		UBICON (Anticipatory ubiquitous computing)	RFID tags, Bluetooth signal
		Traffic congestion prediction	GPS
		Complex event processing	RFID, GPS
		Mode transportation prediction	Crowdsourced data
		Mobility prediction	Smart card
		Mining the semantics of ongin-destination flows	GPS, mobile phone
		Optimizing the mobility models and communication performance	GPS
		CarStream services	Driving data including vehicle status, driver activity, and passenger-trip information
		Traffic monitoring and alert notification	Geo-location and speed data
		Transportation network optimization	GIS and the Internet of Multimedia
		Emissions and traffic-related impacts	Crowdsourced data
		Multi access physical monitoring system	wearable smart-log data
		Wearable health monitoring system..	RFID, Electrocardiogram (ECG) sensor, body temperature sensor, blood pressure sensor
		Early detection of Alzheimer disease	Motion sensor data
	Near real-time	Transportation planning	Bluetooth signal
	Real-time	Transportation planning	Phone camera

3 | Predictive Learning Model

Expectation is about change, i.e., sensing the future. From an IoMT perspective, we need to be able to obtain data streams that can be used to sense a comprehensive context in space and time and infer predictive actions based on predictions of the future state of this context. To this end, *Fig. 1* illustrates the four main steps in building predictive learning models: 1) context sensing, 2) context intelligence, 3) context prediction, and 4) predictive action/feedback loop, as previously proposed. Most advanced research is currently limited to the first three steps. Pejovic and Musolissi [26] stated that the main obstacle to the further proliferation of predictive computing is the inability of IoMT devices (And the IoT s in general) to seamlessly interact with humans and provide feedback, which is critical to guiding the predictive learning process. The literature review presented in this paper also reveals another obstacle to the proliferation of predictive learning models: the lack of approaches to represent a priori spatiotemporal knowledge of a specific context. This is crucial to prevent the "useless" mobile Internet from driving predictive learning processes in the near future.

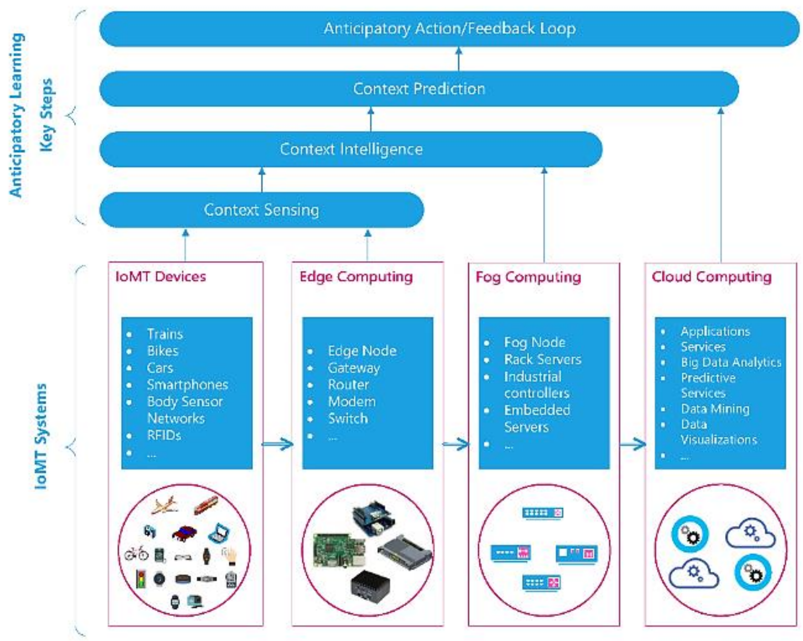

Fig. 1. Overview of the main steps in building predictive learning models using internet of mobile things systems.

4 | Context Sensing at the Edge of a Network

Sensing is essential in providing the data used to generate context intelligence for a predictive learning model. Context may be divided into different categories (Location, identity, activity, time) and may have multiple aspects, such as geographical, physical, social, and temporal. Contextual sensing aims to create an interface between IoMT devices (Things) in the physical world and an individual or group of individuals.

In automotive context sensing, IoMT devices in a vehicle can detect important aspects of driver behavior and the surrounding environment over time. In-vehicle sensors and sensors embedded in mobile devices carried by the driver can also be used to collect IoMT data streams. In addition, IoMT data streams from different vehicles can provide more spatial coverage for better context understanding and can also help reduce disambiguation. Context sensing can provide information about driver lane changes, stop signs, obstacles, and potholes. These features can be further used to infer context fed into a predictive learning model to improve driver safety and engine efficiency.

To achieve this goal, data preprocessing is essential to extract features from IoMT data streams and use those features to provide context intelligence. The availability of edge computing power will allow us to run many preprocessing techniques near the IoMT device rather than sending all IoMT data streams to a data center. The correct selection of preprocessing techniques will be crucial in the subsequent stages of building a predictive learning model. A brief description of each preprocessing step is provided below:

I. Dealing with missing data: For a large aggregated data stream, dropping observations based on missing values is usually not considered a problem, but for a continuous data stream, it may affect our next steps in learning the prediction. Therefore, missing values can be replaced based on the prediction models.

II. Filtering: IoMT devices typically produce noisy data streams. To minimize the impact on the next steps, a clear set of automated tasks to define, detect, and correct errors is needed. Some new approaches can be derived.

III. Summarization and aggregation: For some applications, the summary form of the aggregated data stream may be sufficient for statistical analysis. Other applications may require data aggregation to reduce bandwidth consumption and data latency.

IV. Cleaning: IoMT data streams sometimes produce irrelevant or incorrect data. Cleaning techniques reduce computational time and complexity and improve the predictive model's performance, resulting in fewer data features.

V. Transformation: To deal with the complexity of IoMT data streams, Principal Component Analysis (PCA) is a common technique to reduce the number of data features. Another method, Latent Dirichlet Allocation (LDA), is used to find a linear combination of features that characterizes or separates two or more classes. Pattern Reduction (PR) has recently been proposed to reduce the number of patterns.

It is very important that IoMT data streams are preprocessed before passing to the next stage (i.e., context intelligence). Should we move all our IoMT data to the cloud (Data centers)? Our answer to this question is negative. The closer the preprocessing is to the data source, the more benefits the IoMT system has. With the massive volume of IoMT data streams generated by various sensors, it is possible to flood and drown the networks and data centers (i.e., the cloud). In addition, some preprocessing tasks can be performed using a specific set of IoMT devices, which can help improve the interaction between devices and improve the efficiency of the entire system.

5 | Contextual Intelligence in the Fog Layer of a Network

Contextual intelligence requires inductive reasoning to infer higher-level concepts from preprocessed IoMT data streams. This is not a new theory, with academic references dating back to the early 1980s. However, IoMT systems have shown that contextual intelligence requires predictive learning models that understand the limitations of our algorithms in generating new knowledge and can adapt this knowledge to an environment different from the one in which the learning model was trained. Contextual intelligence requires moving far beyond the analysis of economic, urban, rural, and many other spaces. It is common to rely on simple explanations for complex high-level concepts (i.e., complex phenomena such as human behavior).

Our vision of context intelligence is to distribute flow analytics in a hierarchical order, starting with descriptive analytics, which can be processed at the edge nodes (i.e., gateways) and perform more complex diagnostic analytics on fog nodes. Bonomi et al. previously proposed a hierarchical distributed architecture based on fog computing for low-latency processing of IoT data, location awareness, and mobility support. We extend this distributed architecture with the following elements:

I. Scalability: By distributing automated analytical tasks, context intelligence depends on the scalability of IoMT devices. Many context models require simple machine learning algorithms such as the Linear Spanish Inspection Protocol (L-SIP), which is implemented to reduce data transmission. Filtered state classification (ClassAct) as a human state/activity classifier based on a decision tree and discounted histogram coding (Bare Necessities) used to summarize the relative time spent in given contexts.

II. Mobility and geographical distribution are essential requirements for context intelligence. However, a predictive learning system also requires a rich scenario of communication and interaction between all available computational resources. To achieve this, a priori data pipelines must be designed to support a ubiquitous analytical framework.

III. Heterogeneity and interoperability: The terminal devices in the IoMT system can collect data with different time stamps, formats, and locations. In addition, edge network computing devices that deploy IoT gateways can seamlessly support interoperability between terminal devices. For example, a set of devices, including an armband sensor, a Bluetooth headset, a smartphone, an external antenna for a GPS receiver, and a lightweight laptop with a transceiver, were combined to collect human activity data, which were then processed. Predict the context around them.

6 | Forecasting Context and Forecasting Actions

Context prediction and predictive action are two essential steps for predictive learning models. Predictive action refers to action (Behavior), including actual decision-making. Internal preparation mechanisms, or learning, depend on predictions, expectations, goals, or beliefs about future states. Prediction focuses on the effect of a prediction or expectation on current behavior. In other words, predictive actions are not only about predicting the future or expecting a future event but also about changing behavior (Or behavioral biases and dispositions) based on this prediction or expectation. For predictive learning models to help citizens change their behavior, context prediction and intelligence-based actions must play a central role.

Previous research has described various predictive models used to predict people's or IoMT devices' behavior. Tsai et al. [30] provide a brief overview of data mining techniques for IoT systems. *Fig. 2* shows the state of the art in predictive research using different analytical algorithms and types of data sources, while *Table 2* below summarizes the approaches used to build a predictive model based on supervised and unsupervised predictive techniques. Supervised techniques rely on labeled data and training to find a model that can be applied to a new dataset. In contrast, unsupervised techniques use unlabeled data and try to predict common patterns.

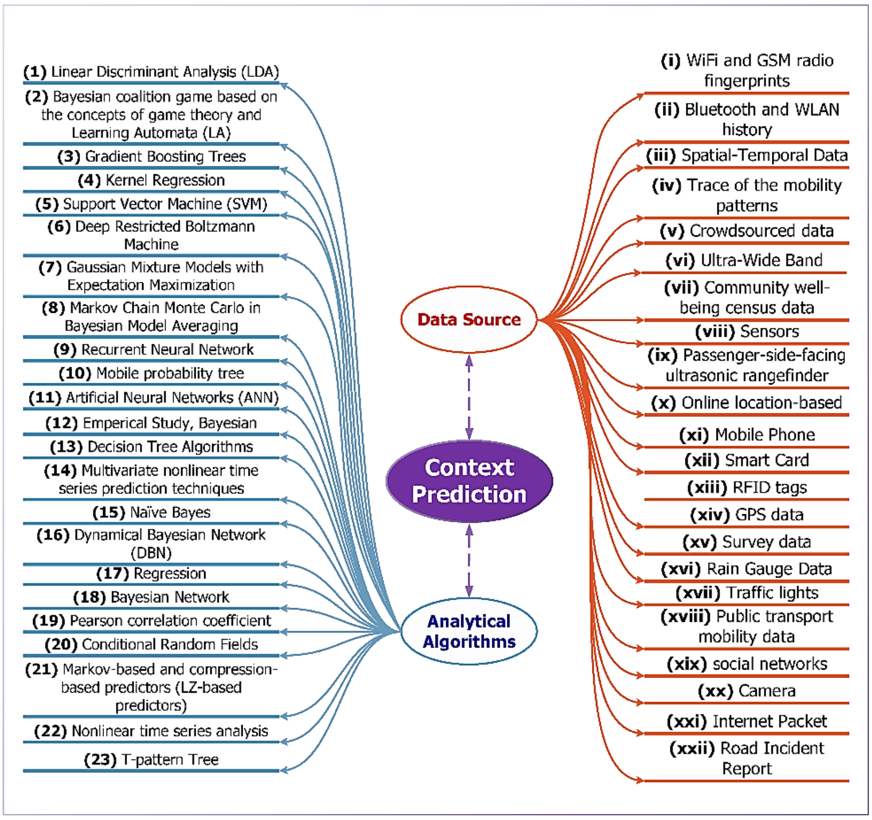

Fig. 2. Overview of different approaches developed for predictive models.

7 | Research Challenges and Opportunities

While the principles of predictive learning modeling have been studied for decades, IoMT is in its infancy. Although recently, researchers have attempted to integrate a predictive process into artificial learning systems, few efforts are found on research applications that apply predictive computing theory to build contextual intelligence in IoMT devices. The proliferation of IoMT devices has created a unique opportunity to explore predictive learning models using the vast volume of IoMT data streams. This section discusses the research challenges in applying predictive computing to IoMT systems.

7.1 | Research Challenges

Predictive learning for IoMT systems relies on multidisciplinary research fields such as the IoT, big data analytics, spatial data science, cloud computing, edge computing, machine learning, and data mining. The challenges inherent in this topic are discussed below.

I. Privacy: One of the main concerns about deploying IoMT devices around a smart city is how to generate predictive actions from IoMT data streams without violating user privacy. Some examples of sensitive information IoMT devices collect include locations, activities, and sentiment. For instance, predictive computing can be misused to predict an individual's future locations or user activities. Privacy becomes more complicated when it comes to considering conflicting privacy policies among multiple users. An example involves a user who may only want to donate one type of data (i.e., Bluetooth data), while another may donate two types (e.g., Bluetooth and Wi-Fi usage data). When this data is combined, and co-location patterns are found, the first user's information can be inadvertently exposed.

II. Security: The diversity of IoMT devices we expect in smart cities poses a significant challenge to protecting the predicted learning process, especially with wearable devices, body sensor networks, or carried items (Such as smartphones). IoMT devices may threaten users due to their susceptibility to hacking. Although there is currently attention paid to the security issue for IoMT systems, there is no common standard, protocol, or security framework for IoMT devices. Therefore, addressing security issues for IoMT is now an urgent concern in our research work.

III. Connectivity: One key factor for making IoMT devices efficient is the communication networks they use. Mobility is a challenge in maintaining a stable connection between IoMT devices in a smart city. New networking technology is expected to keep IoMT devices in seamless data collection, regardless of location, over short and long periods.

IV. Chaos: Unlike fixed location-based IoT devices, device mobility typically creates chaotic and unstable interactions between them. For example, IoT devices at a fixed location always know which neighbors they communicate with. In contrast, IoMT devices are unaware of their immediate neighbors. The first law of geography needs to be further explored regarding the potential impact of geographic proximity on interoperability, power consumption, automation of analytical tasks, data pipelines, and communication protocols of IoMT devices.

V. Management: Choosing the right type of IoMT device to support a specific forecasting task is not easy. Choosing too many IoMT devices may cause problems, such as power drain, noise, and data latency. On the other hand, if fewer devices, edge nodes, and fog nodes are deployed over a large geographic area, there may be gaps in data collection. Another challenge is managing the energy consumption patterns of IoMT devices while they are moving.

VI. Information loss: Processing data streams at the edge of a network carries potential information loss. This risk must be balanced between system efficiency and the value of the lost contextual information. It also raises an important question about the potential geographic divide, where regions of a smart city determine which data streams should be processed at edge nodes and which data streams should be processed in a cloud computing environment. Determining the type of data stream and mobility behavior of IoMT devices and where they should be used for data processing is an interesting research challenge.

VII. Geospatial steaming: Analyzing the spatial relationship between locations of measured contextual variables using a sequence of aggregated data streams requires new methods that do not rely on density and proximity but rather on connecting a massive cloud of data points. The research challenge is threefold: 1) developing new spatial interpolation processes to determine which data points from current data streams should be used to estimate values at other unknown points, 2) how do you choose the type of time window for the geospatial analysis flow? and 3) geospatial summarization, where the connectivity of IoMT devices is used to summarize the accumulated data streams in space and time.

VIII. D. ubiquitous analytics frameworks: From our literature review, more than 400 architectures have been developed to manage incoming IoT data streams using different strategies, such as streaming, micro-batch, and batch processing. These strategies are designed to work towards an asynchronous approach for static IoT devices. To develop predictive learning models using IoMT systems, we identified the need for ubiquitous analytics frameworks capable of breaking down processing and analytics capabilities into a network of streaming tasks and distributing them across different computing nodes in an edge-fog-cloud continuum. The research challenge is to develop location-aware analytics capabilities to support descriptive, diagnostic, and predictive streaming analytics.

7.2 | Opportunities

Alongside the above challenges, there are always opportunities. We illustrate some of these in terms of predictive computing for IoMT systems.

I. Locations offer many opportunities for geospatial research. The ability to sense the context of an IoMT system typically generates data streams that can be used to develop new location-aware applications. The mobility of these devices can also be investigated using different spatial and temporal scales. New location and mobility prediction models are needed to support predictive learning models, especially in the case of smart cities.

II. Real-time predictive actions: Having a learning engine close to the IoMT device and combining knowledge and insights computed in a cloud environment can predict the needs of citizens in real-time. As explained, if this real-time analysis is fed into some predictive model and the results are used to make current user decisions, then we have what is defined as predictive computing. If the output of the predictive model is fed directly into an automated decision-making process, it guarantees the desired outcome. This is prescriptive analytics. This roadmap essentially shapes the future.

III. Integration with opportunistic computing: There is a concern about how users carrying IoMT devices can interact with each other opportunistically. IoMT can be an enabler by enabling more user interaction through mobile devices. Some typical applications include human-centric sensing and data sharing.

IV. Blending different research fields to mimic human predictive actions: Recently, digital assistants like Apple Siri, Google Now, and Microsoft Cortana have been able to help people with tasks like sending a text, playing a song, adding a reminder, etc. None of these tasks require predictive actions. Researchers seek tools to deliver instantaneously, understand the context, and analyze massive data streams. To achieve this goal, predictive computing combines many research fields, such as geography, deep learning, humanoid robots, artificial general intelligence, and big data analytics.

8 | Conclusion

Predictive learning, as a powerful approach to data analysis and prediction of future events, can play an important role in improving the performance of MIoT systems. However, several challenges, such as mobility, resource constraints, the need for real-time processing, and security issues, require further research. The development of lightweight algorithms, adaptive learning, edge processing, and security methods are among the important research opportunities in this area. Also, predictive learning, as a key approach in the MIoT, provides the ability to predict future events and optimize the performance of systems. Challenges such as mobility, resource constraints, and the need for real-time processing require further research. The development of new methods such as federated learning, deep reinforcement learning, and edge processing have created important research opportunities in this area. Given the rapid growth of MIoT and artificial intelligence technologies, predictive learning is expected to play an important role in shaping the future of the MIoT. This paper discusses predictive computing, which refers to systems that focus on predicting what is most relevant to users and acting on it rather than just reacting to user commands. Predictive actions rely on different models, combining processing layers such as cloud, edge, and fog nodes deployed around a smart city. It is important to note that predictive computing systems and IoMT are constantly evolving. Furthermore, the proliferation of IoMT devices presents many related research challenges and opportunities, which are discussed in this paper. The promising trend towards IoMT and IoT in general has already attracted researchers from various industries, academic disciplines, research groups, government agencies, etc., who are building the foundations of smart cities. We have identified a gap in this foundation: predictive actions, which are expected to impact how smart cities will function. The path outlined in this article will provide useful guidelines for further research into this emerging topic.

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Conflicts of Interest

The authors have not explicitly declared any conflicts of interest in the document

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