1*Rawan Sanyour

2Manal Abdullah

QoIoTX: A QoE-Aware IoT Service Discovery Framework

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Abstract: - Quality of Experience QoE is a research area that evaluates performance based on subjective and objective metrics for the use of a product or a service. Currently, the substantial majority of QoE works mainly focus on multimedia services. However, the introduction of Internet of Things IoT has brought a new level of complexity into the field of QoE evaluation. With the evolution of new IoT technologies such as machine to machine communication and artificial intelligence, utilizing additional evaluation factors alongside the traditional ones is a crucial demand. This paper proposes QoIoTX, a QoE-based service discovery framework that can be utilized to evaluate the QoE of IoT service/application on the fly considering multiple parameters about data, network, users, and services. It extends the conventional QoE and goes beyond its legacy evaluation phases. Also, provides a novel alternative approach to evaluate the IoT services subjectively rather than using the traditional approaches that do not cope with the rapidly evolving services. Although each of the identified QoE factors is measured on a different scale and may involve different units of measurement, the proposed work can effectively evaluate the QoE through providing a single value that represents the acceptability degree of each service

Keywords: Quality of Experience QoE, Quality of Data QoD, Quality of Network QoN, Quality of Context QoC, User Context, Utility Function.

1. Introduction

Internet of Things IoT can be depicted as a collection of smart, self-configuring, and uniquely addressable objects that have sensing, networking, and processing capabilities which allow them to communicate with other devices and services over the Internet to perform some specific tasks [1,2]. According to [3], the ever-growing connected devices was forecasted to be around 3 billion at the end of 2023 and expected to reach 6 billion by 2029. The growth of massive IoT technologies is gradually shifted from simple sensors and actuators into advance services and applications that extensively use the tremendous amount of data generated by such devices to provide new facilities utilized by citizens, companies, and public administrations [4]. The ultimate aim of IoT is to effectively incorporate technologies into our everyday lives through including networking and social interactions between physical and virtual components. In recent years, the massive number of IoT innovative services are adopted on various platforms to play essential roles in various fields such as transportation, smart cities, smart buildings, healthcare, energy management, etc. The rapid increase of the large number of heterogeneous connected devices comes with a series of issues related to network, security, data government, complex users' requirements and the perceived services' quality. Such different devices have different processing power, storage capacity, energy consumption, and utilize different technologies and communication protocols. The heterogeneity of these underlying resources has its own unique characteristics, thus making the IoT paradigm a challenging domain for quality evaluation.

The evaluation of the IoT services and applications performance becomes essential as they are ubiquitously utilized in our everyday life scenarios. However, as the IoT field is massively growing, giving some guidelines to follow to perform such processes is very complicated in rapidly changing environment. Often, Quality of Experience QoE is the most common metric that has been utilized for the purpose of quality evaluation. It is simply defined as *"the degree of delight or annoyance of the user of an application or service."* [5]. This concept is closely related to human experience; thus, its prime focus is to assess the user's satisfaction, i.e. how the user subjectively perceives the intended service/application quality. For long, QoE is extensively utilized within multimedia domain to fulfill the network quality requirements through Quality-of-Service QoS evaluation metrics including network delay, jitter, packet drops, and bandwidth [6,7].

1,2Information System Department, Faculty of Computing and Information Technology, King Abdul Aziz University, Jeddah, Saudi Arabia,*
**Email: Rsanyour0001@stu.kau.edu.sa, Email: Maaabdullah@kau.edu.sa*

However, such metrics do not capture or reflect the overall acceptability of the intended service/application as they tend to evaluate the Machine-To-Machine M2M aspects, i.e., aspects that cover the data exchange among objects within the system [8]. The pervasive nature of the emerging IoT services involves the end user as primary player who directly engaged in the loop, thus, aspects such as Human-To- Machine/Machine-To-Human H2M/M2H should be considered when evaluating the QoE. To this end, it is clear that the idea of extending the QoE evaluation to combine the basic principles of the traditional QoE along with other influential factors that cover the entire M2M, M2H, H2M communication scenarios is an urgent demand that forms the core part of this research.

The novelty of this work is to deviate from the conventional QoE evaluation paradigm and go beyond the legacy QoS techniques. This can be achieved through addressing the evaluation of QoE in IoT services from two distinct but often complementary perspectives: objective, and subjective quality assessment. In addition to evaluating the traditional QoS metrics, i.e., evaluating the network performance and its impact on the user's quality perception, other objective influential factors are introduced for QoE evaluation. Quality of Data QoD is one of these factors which refers to the quality of acquired data at the sensing stage. It consists of data accuracy, data truthfulness, data completeness, and data up-to-dateness [9]. Another factor is the Quality of User Context QoUC. The word context refers to information that can be utilized to represent the state of an entity, thus, can be utilized to provide adequate services (i.e., expected service) to the end user. Buchholz et al. [10] identified QoC as any information that can be used to ensure the quality of the context information. Ensuring the quality of context allows service providers to provide services that are suitable for users' certain circumstances, thus, efficiently enhance the system performance. As conducting subjective tests seems to be no longer appropriate choice to evaluate the QoE subjectively in the IoT paradigm due to several reasons First, with the massive diversity in number and type of existing IoT services it became infeasible to conduct a subjective test for every existing and new service and application. Even if objective models are built based on a conducted subjective test, they will become valid only for the related specific scenario for which the models were built. Second, as the application scenarios of the multimedia domain and IoT domain are vastly different, it is not possible to extend the existing multimedia QoE evaluation standardization into the IoT context. Third, the dynamism nature of the IoT environment forces to introduce a new level of influential factors to cope with such dynamicity. Other alternative approaches are considered to evaluate the IoT services/applications subjectively. Current IoT services/applications already collect information regarding their users. Such information can be useful to understand the degree of satisfaction the user has regarding this service/application. In this work, information such as usage data is utilized to understand the behavior of the user with the intended service. This can provide useful insights into user satisfaction without the need for conducting subjective tests. The two fields, IoT and QoE were merged to model, measure, and evaluate the QoE of IoT services. Following, we describe the two main contributions of this research.

- **The QoE evaluation model to measure and estimate QoE.** The QoE evaluation module is a module to evaluate the overall QoE for IoT services/ applications in which humans play an essential role as end users. The proposed architecture is a two-layer architecture: measurement layer to evaluate different QoE influencing factors separately to be combined to estimate the final quality value that would be perceived by the user, and prediction layer to estimate the overall QoIoTX through a two-tier utility equation that combines the different QoE indicators as a linear weighted sum of multiple evaluated factors.

- **A QoE-aware service discovery framework for smart spaces.** a QoE-aware service discovery framework for smart spaces within which a model that evaluates the overall QoE in IoT services/ applications is proposed. It can be utilized to dynamically discover IoT services in smart spaces and generate a list of situation-aware services ranked according to their evaluated acceptability degree values. It is composed of three main subcomponents: service matching manager that receives users requests, the context manager component which is responsible for deriving the user's related context information attached with the probability of correctness that represents the confidence level of this derived data, and the QoE manager that estimates the acceptability degree of each requested service and ranks these services accordingly.

2. Materials and methods

This work introduces the QoIoTX framework, a QoE-aware service discovery framework that can be utilized to dynamically discover IoT services in smart spaces and generate a list of situation-aware services ranked according to their evaluated acceptability degree values. Essentially, the QoIoTX is an aggregation of metrics which are measured from two different perspectives: 1) Quality of Things factors QoTX which includes objective evaluation factors, and 2) Quality of Human Factors QoHX that consists of the subjective human factors. A high-level overview of QoIoTX is illustrated in Figure 1 and can be formally expressed as:

Definition (QoIoTX) *is an aggregate value of various IoT quality metrics that estimate the overall delivered quality of an IoT service/application. The perceived quality is evaluated as a combination of the evaluated set of the identified subjective and objective QoE influencing indicators.*

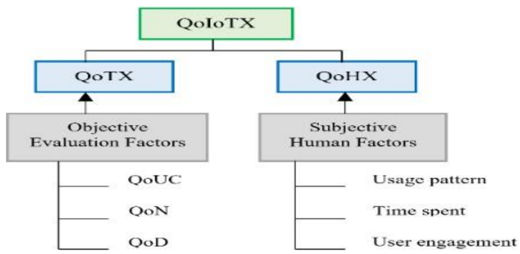


Fig. 1 QoIoTX as a Combination of QoTX and QoHX

As shown in the figure, the QoIoTX is evaluated as a combination of two categorized factors: the objective evaluation factors QoTX by which the quality of data, network and context metrics are objectively evaluated, and the subjective human factors QoHX such as usage patterns including time spent using the service/application, No. of times users used the services, and user engagement (No. of functions used).

2.1. System Architecture

Figure2 introduces the QoIoTX framework within which the QoE model is proposed. This work considers smart spaces as entities that offer services to users (e.g., transportation services, weather services, traffic detection services, parking services, etc.). These services are supported by IoT objects to deliver useful information such as bus station schedule, near parking slots, available taxi nearby, etc. Users are represented through their mobiles and can request these services to support their activities. For example, a user may want to discover the best service for transportation reservation in a smart place where he resides. As this work focuses on the QoE-based discovery of IoT services, this user will receive a list of services ranked according to the estimated acceptability degree value as a response.

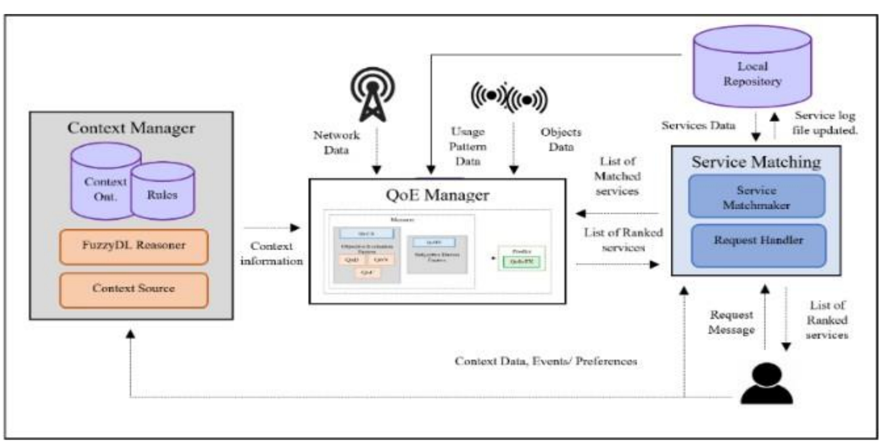


Fig 2 The Proposed QoIoTX Service Discovery Framework – Detailed Architecture

2.2. QoIoTX framework components

QoIoTX is a QoE-aware framework for service discovery in smart spaces (Figure2). It is composed of three main components. The request handler in the service matching manager receives requests and tries to solve them using the service matchmaker module which searches for services in the local repository. If requests are solved, a list of matched services will be sent to the QoE manager to evaluate their overall QoIoTX value and returns the response back to the user as a list of matched services ranked according to their estimated acceptability degree values. The following sections explain how these components interact to achieve an efficient discovery.

2.2.1. Service matching manager

This manager is responsible for receiving the users' requests, searching for the matched services registered in the repository, updating the service's log file, sending the list of matched services to the QoE manager, and sending the list of ranked services back to the user. The service discovery process starts when the request handler receives a request from a consumer. Then, the manager tries to solve the request using the service matchmaker module, which searches for services in the local repository based on consumers' request. When the matched services list is found, it will be sent to the QoE manager to estimate their overall QoIoTX values. The values of Frequency of use, and Comprehensiveness of use in the service log file will be updated as well. The service matching manager uses the following definitions to realize these processes.

- **Definition (Service$_{req}$)** A service request is defined as Service$_{req}$ = *{UID, I, O, D}* consisting of user's ID, request input's types, outputs' types and domains.
- **Definition (Response$_{msg}$)** A request response message is used to send the response to consumers and is defined as Res$_{msg}$ = *{UID, r, RESTime, REQsize}* where UID is the user identifier, r consumer' request, RESTime is the response time, and REQsize is the request size.

It is composed by two main subcomponents as follows:

- Request handler: This component receives requests from consumers consisting of user's ID, request input's types, output's types and domains. The role of the request handler is to extract these properties from this request. It is also responsible for generating responses in which each response is message in the form Response$_{msg}$ = *{UID, r, RESTime, REQsize}.*
- Service Matchmaker: This component implements semantic and syntactic methods to compare services and requests parameters. It uses the semantic annotations from the service repository, i.e., service ontology to match this information. The match between requests and services is made based on the match between inputs and outputs of the functional description. When the factors of the service request input and the service description input match each other, the two inputs match, and when parameters of the service request output and parameters of the service description output match each other, the two outputs match. The matchmaker module uses the matching methods already defined in the literature to discover relations between services inputs and outputs [11].

2.2.2. Context manager

As a part of the proposed framework, evaluating the QoUC is an essential phase to estimate the overall QoE for a requested IoT service/application. This component is responsible for deriving the user's related context information using realtime context data and calendar/preferences data. Figure 4 shows the detailed context manager architecture for developing the fuzzy rough ontology which will be utilized to derive the user's context information. The context manager component is constructed in two main phases. First, we built the fuzzy rough ontology using Protégé 4.3, OWL2 and fuzzy annotation properties through FuzzyOWL2 plug-in and following the FUZRUF-onto methodology [12]. The output of this phase is a validated ontology. Second, we reasoned and queried the constructed fuzzy rough ontology using FuzzyDL with the user's real time context data retrieved from his profile, calendar, and preferences. Figure 3 depicts the detailed Context Manager Architecture.

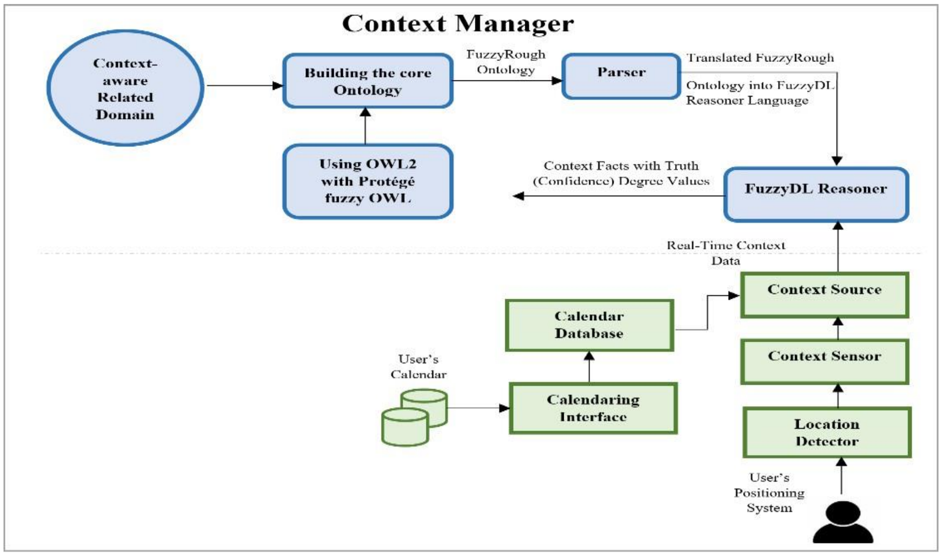


Fig 3. QoE-aware service discovery framework - Context Manager Architecture

2.2.2.1. Phase 1: Building the fuzzy rough ontology.

In this section, we propose a novel fuzzy rough context ontology that can effectively model the user's context in real time. QoIoTX needs to formalize the user's realtime context in a model that can be utilized to deduce the current status and represents the different context concepts in a way that allows to reflect the real time situation for a specific user. The context manager creates fuzzy rough ontology that defines context's concepts and their relationships in the targeted service discovery domain. The developed ontology is constructed following the FUZRUF-onto methodology through three different steps: building the typical ontology components, i.e., the crisp parts using Protégé 4.3, and representing the fuzzy rough components using the Fuzzy OWL2 2.3 plug-in[1] in Protégé 4.3 that allows to create Fuzzy OWL2 ontologies. This tool does not directly translate the fuzzy representations into OWL2 Language, but rather, allows for specifying the type of fuzzy logic used, defining fuzzy data types, fuzzy modified concepts, weighted concepts, weighted sum concepts, fuzzy modifiers, fuzzy modified roles and data types, and fuzzy axioms [13]. In Fuzzy OWL2, there are three fundamental concepts are considered: Concepts, roles, and Individuals. These symbols are represented in an ontology as classes, relations, and individuals respectively.

Context sources*:* Raw contextual data is processed using specialized developed modules. This processing step is achieved by the context source module as shown in figure4. User's position and calendar data are the primary real-time context data to be utilized in order to infer his current context situation. User's position is detected using a positioning system at user's side, i.e., his device. Location estimation is accomplished using GAIA GPS2 , a GPS-based tool by which user's location data such as latitude, longitude, moving speed, elevation, distance and time in different indoor/outdoor location scenarios are specified with possibility to specify the activity performed by the user at that moment. Such data is represented using GPX[3] (GPS exchange format), a light-weight open- source XML data format for the interchange of GPS data (waypoints, routes, and tracks) between applications and Web services on the Internet. Note that user's speed data is not included in the original GPX data file, instead, it is saved in the track info in the tool application itself. Therefore, the GPX waypoint sent by the tool is enriched with information about user's speed. Listing 1 illustrates an example of a GPX waypoint collected by the position detection tool enriched by user's speed(k/h).

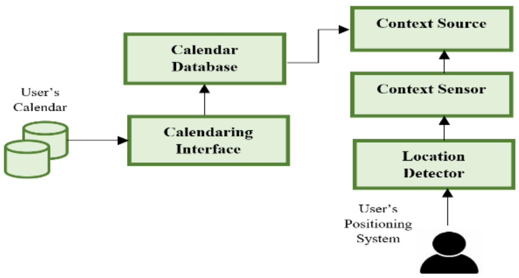


Fig 4. The Context Sources Module


```
<trkpt lat="24.499762" lon="39.663717">
  <ele>613.6</ele>
  <time>2023-01-20T17:44:35Z</time>
  <speed> 0.8 </speed>
 </trkpt>
```


Listing 1: A fragment of a GPX Waypoint Containing the User Position and Speed

The calendaring interface module allows to access user's personal calendars, locate exactly his appointments and events, thus, compare that location with his current location. A java-based application is developed to retrieve user's calendar, and the related appointments and events stored in his calendar. The retrieved information then, is stored in JSON format.

The developed ontology is validated using the FuzzyDL reasoner, and consists of 96 classes/sub-classes, 24 fuzzy datatypes, 24 data properties, 8 object properties, and 4 test individuals, and expressed in $\mathcal{SROIQ}(\mathcal{D})$ $\mathcal{DL}$ expressive model. Following some of identified scenarios by which different users with different objectives, roles, and context situations in both indoor/outdoor environments are defined.

2.2.2.2. Phase 2: Querying the fuzzy rough ontology.

Using the installed plugin and Gurobi software[4], a prescriptive analytics solver and a decision-making technology that uses mathematical optimization to calculate the answer to a problem, we can send queries in specified syntax and predefined tags to our constructed fuzzy ontology and get fuzzy answers. Four different scenarios in which four different users roles with different context situations are identified. These users are supposed to request various IoT services that are available in their surrounding area. For each identified scenario, some parameters such as user's current time, location, speed, events, actions, and other user's context information are detected.

- **Scenario 1: A traveler who is in an airport.** Suppose that we have a user with the role *Traveler* in an *Airport* looking for some available services nearby. Based on this information, the different ontology components are defined.
- **Scenario 2: A tourist who is in a Restaurant.** A user with the role of *Visitor* in a *Restaurant* looking for a transportation service, traffic detection services, and/or some activity services nearby. Based on this information, the different ontology components are defined.
- **Scenario 3: A Tourist who is searching for activity services.** A user with the role *Tourist* looking for near- by activity services. Based on this information, the different ontology components are defined.
- **Scenario 4: A User who has an upcoming event.** A user with the role of *Lecturer* looking for nearby services. Based on this information, the different ontology components are defined.

[1] http://www.umbertostraccia.it/cs/software/fuzzyDL/fuzzyDL.html
[2] https://www.gaiagps.com/
[3] https://www.topografix.com/gpx.asp
[4] https://www.gurobi.com/downloads/gurobi-software/

2.2.3. QoE manager

The QoE manager architecture as shown in figure 5, is a two-layer architecture: measurement layer and prediction layer. It provides a two-step evaluation of QoE in which a separation of roles within the evaluation processes is presented. The input parameters include dynamic information that the model reasons on it. It includes raw data produced from IoT objects, real time network data, user's context information, and user's service usage patterns.

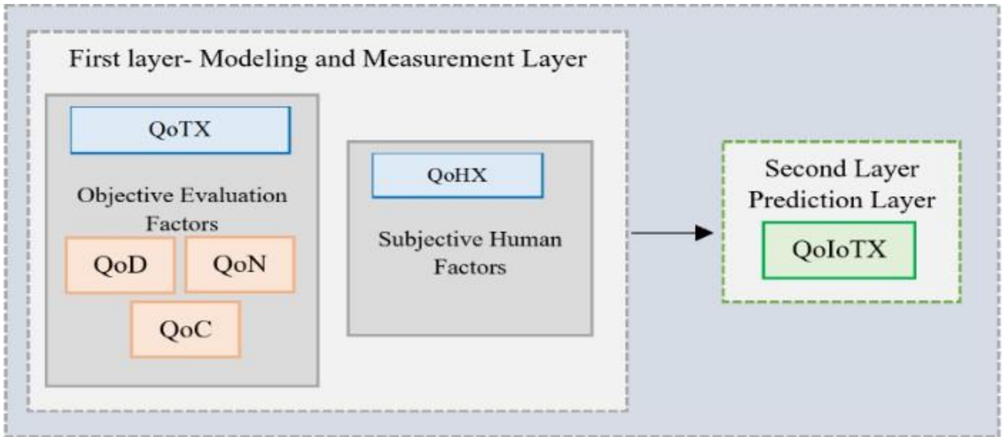


Fig 5. QoE Manager Architecture

2.2.3.1. First layer - Modeling and measurement layer

The ultimate objective of this layer is to evaluate different QoE influencing factors separately to be combined to estimate the final QoE value that would be perceived by the end user. As illustrated in figure 6, the measurement layer is composed of two sublayers categorized by quality influencing factors: the Quality of Things Experience which encompasses the objective evaluation factors by which the quality of data, network and context metrics are objectively evaluated, and the Quality of Human Experience that includes the subjective human factors such as usage pattern data including time spent using the service/application, No. of times users used the services, and user engagement (No. of functions used).

a) Quality of Things Experience QoTX Sub-Layer

- **Evaluating Quality of Data QoD.** Erroneous data can arise from different hardware and/or software sources leading to faulty decisions, business losses and maybe life-threatening situations [14]. In the IoT environment, a sensor's outlier can be defined as" an irregularity or a divergence in sensor behaviour when compared to its previous behaviour or readings" [15]. Castillo and Thierer [16] have defined an outlier as "a data point which is significantly different from other data points, or does not conform to the expected normal behaviour, or conforms well to a defined abnormal behaviour". There are three common types of outliers in IoT sensors: 1) intrinsic sensor or binary faults which are impaired readings produced from faulty devices [17]. 2) sensor events which are unforeseen changes caused by unlikely situations that severely affect the sensor, therefore, generating outliers.
3) device errors generated by some intermittent events such as theft and malicious attacks. Detecting such outliers can effectively enhance the quality of generated data, thus, positively impacting the decision-making processes [14 – 17]. The input of this layer is the sensed data, and the output is the accuracy percentage of such data.

- **Evaluating Quality of Network QoN.** At this layer, the QoS parameters such as throughput will be utilized to evaluate the performance of the underlying network as they are the most important metrics that traditionally have been linked to QoS and QoE research. The real-time analysis of such metrics allows to deduce significant information regarding potential network failure, performance estimation, load balancing, resource management and congestion prediction. According to [21], throughput can be considered as one of the most significant metrics that affect end users' service perception. The input of this layer is the collected network statistics including throughput at the source node and the output is the evaluated network reliability.

- **Evaluating Quality of User Context QoUC.** Context awareness is one of the fundamental aspects in IoT applications. In such applications, raw data that is sensed by IoT devices can be considered as the base from which the context information is extracted. The word context refers to the information of the current situation that is utilized to provide adequate services (i.e., expected service) to the end user. Buchholz et al. [10] identified QoC as any information that can be used to ensure the quality of the context information. Ensuring the quality of context allows service providers to provide services that are suitable for users' certain circumstances, thus, efficiently enhance the system performance. QoC can be assessed either subjectively by illustrating to what extent a piece of context information meets the requirements of the application consumer or objectively by determining the characteristics of the devices by which the context data is collected. One of the main quantifiable QoC evaluation criteria is the confidence level (the probability of correctness). Confidence is a numeric value attached to the context information by which the degree of certainty for context information trustworthiness is declared. The built Fuzzy rough ontology is used to infer this value of confidence. The input of this layer is context data, and the output is the user's context information accompanied with the probability of correctness, i.e., confidence level.

b) Quality of Human Experience QoHX Sub-Layer

IoT applications and services already collect significant information regarding their users. Such information can be utilized to understand their behavior and the degree of satisfaction they have about the used applications/service. Usage pattern data including time spent using the service/application, No. of times users used the services, and user engagement (No. of functions used) can be considered as acceptability indicators that determine the users' behavior, thus, their quality perception. Statistical machine learning techniques such as multiple leaner regressions will be used to predict service acceptance level and the overall user engagement level accordingly.

2.2.3.2. Second layer - Prediction layer

Two-tier QoIoTX utility equation. The role of this sublayer is to estimate the QoIoTX value through combining the evaluation results from the objective, i.e., things related factors, and subjective, i.e., human related factors. The equation combines the different QoE indicators as a linear weighted sum of multiple factors to define the QoIoTX utility function. The $w_i s$ Coefficients represent the priority (importance) of each factor, and how they affect the overall performance of the QoE evaluation. The result is a single scalar value that can be utilized by the stakeholders, users and developers to 1) adjust prioritize certain QoIoTX metrics, and 2) make significant decisions regarding some issues related to network, programing and performance optimization.

$$\text{QoIoTX} = \underbrace{(w_i\,\text{QoD} + w_i\,\text{QoN} + w_i\,\text{QoUC})}^{\text{Objective Things-related factors (QoTX)}} + \underbrace{w_i\,(\text{User Engagement Level UEL})}^{\text{Subjective Human-related factors (QoHX) (i.e., User Experience)}} \quad (1)$$

a) Objective things-related factors

- **QoD and QoN modeling equations**. There are some Key Performance Indicators KPIs such as reliability, and accuracy that don't have pre-defined measurement methods. Thus, utility theory can be utilized to formalize the relationship between such KPIs and computed low level objective metrics. Utility theory has emerged from macroeconomics theories to formalize the relationship between service performance and low level objective metrics [22] . In the QoE research area, utility functions are often used to map the network related metrics such as delay, throughput, and packet loss directly into MOS scores in video and voice multimedia applications [21,22]. In this work, such utility functions will be utilized to estimate the selected high level performance indicators. For the things-related parts: QoD and QoN, Multi Attribute Utility Function MAUF [25][26] will be used to measure the reliability and accuracy of the network data and sensed data by decomposing its parts into several Single Attribute Utility Functions SAUFs. For each low-level metric x_i , a single attribute utility function U(x_i) will be computed using two types of utility function: exponential (Eq. 2) [23] and sigmoidal (Eq. 3) [27] utility functions, where i=1,2,…, n, represents the number of low level metrics used, c is the maximum value of the utility function, b is the inflection or turning point of the sigmoid, and a is the slope of the sigmoidal curve at the turning point. The static parameters calibration in all equations is performed using Microsoft excel solver in order to find the best fitted values for each of the measurable metrics.

$$U(xi) = a.e^{-b.xi} + c \qquad (2)$$

$$U(xi) = \frac{1}{1+e^{-x}} \qquad (3)$$

After calculating utility function for each QoD and QoN metrics, an additive MAUF in the form of Eq.4 will be used as a linear weighted sum of multiple SAUF, where *xi* is the value of the metric x and *wi* is the relative weight (priority) of that metric and it takes a positive number ranging from 0.0 to 1.0.

$$U\ (x1,\ x2,\dots,xn) = \sum_{i=1}^{n} wi * U(xi) \qquad (4)$$

Note that in the proposed equation, i.e., Eq.1, there are two factors that are directly related to the user: the user context, by which the situation of the user is defined, and the subjective indicators that based upon the IoT service/application usage pattern data.

- **QoUC modeling equation.** In developing context aware services and applications, quality criteria such as reliability of contextual information (the level of accuracy) is crucial. As mentioned earlier, the Quality of User Context QoUC indicates the quality of contextual information that is involved in context-aware decision-making processes at a specific situation. Due to its uncertainty nature, contextual information can be uncertain and incomplete, therefore, using models such as fuzzy rough theory, confidence levels (i.e., Probability of Correctness PrC) can be identified to refer to correctness for any given contextual information. i.e.

$$QoUC = f\ (PrC(a_1), PrC(a_2), PrC(a_3), \dots, PrC(a_n))$$

Using Eq.5, context attributes including location, time, environment, mobility, and activity are mathematically mapped to the overall QoUC probability of correctness value. Let PrC(a_i) denotes the probability of correctness of context attribute a_i, and wi indicates the weight by which the priority of each attribute is identified.

$$QoUC = \sum_{i=1}^{n} wi * PrC(ai) \qquad (5)$$

Eq.5 considers a linear weighted sum of each QoUC attribute to compute the global PrC that can be mapped easily on an interval scale.

b) Subjective human-related factors

Although IoT communications are Machine to Machine M2M-based technologies, in various applications scenarios, humans are involved in some way or another. Therefore, concepts such as Machine to Human M2H or Human to Machine H2M should be considered in evaluating the overall quality of experience of such applications and services. Instead of conducting subjective tests, mining usage data can provide useful insights regarding users' satisfaction. Data such as usage patterns and behaviour can be considered as significant alternatives to reflect the user related subjective factors. Application/service usage data and user actions are examples of these patterns. Each application/service is attached with log files that contain rich information regarding users. For example, when the user uses it, how long he uses it, which are the most commonly used features, etc. Two usage metrics can be extracted from the service log data to be evaluated: Frequency of use, and Comprehensiveness of use.

- **Frequency of use:** it indicates the user level (local) usage pattern as the number of times a service is requested by a specific user.
- **Comprehensiveness of use:** it indicates the service level (global) usage pattern represented by the number of distinct times a service is requested by all users.

In order to extract such information, several processing steps are required to process logs file data. The result of these steps is a service log dataset file ready for further analysis. Each row represents a session for a specific user with information related to user's ID, frequency of use, comprehensiveness of use, and response time for each service request. For modeling the relationship between these factors and the overall User Engagement Level UEL, Multiple linear regression (MLR) is utilized.

$$UEL = \beta 0 + \beta 1X1 + \beta 2X2 \qquad (6)$$

In Eq. 6, $\beta 0$ is the y-intercept (value of y when all other parameters are set to 0), $\beta 1, , \beta 2$ are the coefficients of the independent variables X1, X2 which represent the frequency of use and comprehensiveness of use respectively. The coefficients are calculated and solved using Microsoft Excel Regression tool.

The last step is to aggregate the measured things-related and human-related metrics as a weighted linear combination to determine the single QoIoTX utility values. As the acceptability degree is the ultimate goal to be measured, these estimated values will be mapped into a bipolar interval scale to determine the user's overall acceptability degree using. Figure 6 shows these intervals on the bipolar scale and the assigned degree that match each identified interval. The highest achievable utility value, '1', is mapped to the best possible QoE outcome such as "excellent" and lowest utility value, '0', is mapped to worst possible outcome say, "poor". Similarly, utilities are assigned to other outcomes such as "very good", "good" and "fair", as '0.75', '0.50' and '0.25', respectively.

Interval	The Assigned Degree
[0:0.1250]	Poor
[0.1251:0.3750]	Fair
[0.3751:0.6350]	Good
[0.6351:0.8750]	Very Good
>.8751	Excellent

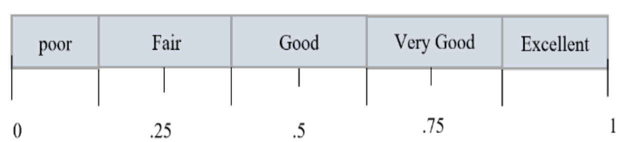


Fig 6. The Bipolar Interval Scale and The Assigned Degree Matched

It is worth noting that organizing the QoIoTX in two tiers is advantageous as it provides a generic structure that can be modified easily depending upon the requirements. For example, if the usage patterns data is not available for any reason, its related part can be eliminated easily by adjusting the attached weight value to be zero, thus, it will not be considered in the evaluation process. In contrast, it is flexible to encompass an additional range of QoE parameters and context attributes to correctly measure and predict users' QoE.

3. Results and discussion

3.1. Evaluation approach

This section presents the evaluation of QoIoTX service discovery framework performance, which measures to what extent can the use of this model improve service discovery efficiency in the IoT service environment, to what extent can the real-time performance of the underlying communication infrastructure affect the overall quality of the requested IoT services, to what extent can the use of fuzzy rough ontologies to improve the overall QoE estimation through enhancing the QoUC factor, and to what extent can the use of services' usage patterns improve the overall QoE through calculating the overall User Engagement Level UEL. The evaluation process was performed by implementing five different service requests in four different scenarios with four different users.

3.2. Experimental Set-up

A prototype of the QoIoTX service discovery model is implemented for this evaluation. This prototype is implemented in Python 3.5 and deployed in a laptop in a centralized manner. Requests are sent using a MQTT broker through Wi-Fi, 4G and 5G networks. During the experiments, the laptop is utilized as a consumer (localhost) to send requests to the services' gateway which is the localhost as well. Services are stored in a Mongo 6.0 database and requested by establishing a MQTT communication through the MQTT broker.

This evaluation measures the discovery efficiency of the implemented work with several services requests according to the metrics defined earlier. The consumer requests a service in each experiment. Each experiment (i.e., a service request) is replicated several times (4,5,6, and 7) to build the service's access log file which each row represents a session for a specific user with information related to user's ID, service name, frequency of use, comprehensiveness of use, and response time for each service. Services dataset is proposed by [28] consists of 1082 services that combined IoT services examples and domains proposed by IoT literature [29], and 946 services which are translated from the OWLS-TC V4. Each service attached with a service description that can be defined as a tuple of service identifier, inputs, outputs, url endpoint, and domain. $Service_{desc}$ = *{ID, I, O, URL, D}*. all the semantic annotations that describe these inputs, outputs, and domains are defined through a set of predefined service ontologies. Users can send service requests that will trigger the discovery process.

3.3. Scenario-based Study

For each scenario, the calculation of the Two-tier QoIoTX utility equation factors (eq. 1) is varied for two different users to examine the impact of such factors to the overall QoE estimation. The first factor, i.e., QoD, is varied by injecting the data with three synthetic anomaly types including instant, bias, and gradual drift. The anomalies are injected supposing that precisely a kind of anomaly is likely to occur to data, thus, the original values are altered accordingly. QoN factor is also varied by considering three types on networks: wi-fi, 4G, and 5G supposing that users use different kinds of networks. The QoUC factor is varied by considering different number of context factors to calculate it each time. Finally, the UEL is also varied by computing the local and/or global UEL. The local UEL is used to indicate the user level (local) usage pattern, while the global UEL is used to indicate the service level (global) usage pattern. Figure 7 depicts the taxonomy of this evaluation process. It consists of two main phases: evaluating each of the influencing factors in eq. 1 through quantifying it to have a value that can be used in the final calculation, and in the second phase, this equation is utilized to calculate the overall QoIoTX utility value to be mapped into a bipolar interval scale to determine the user's overall acceptability degree.

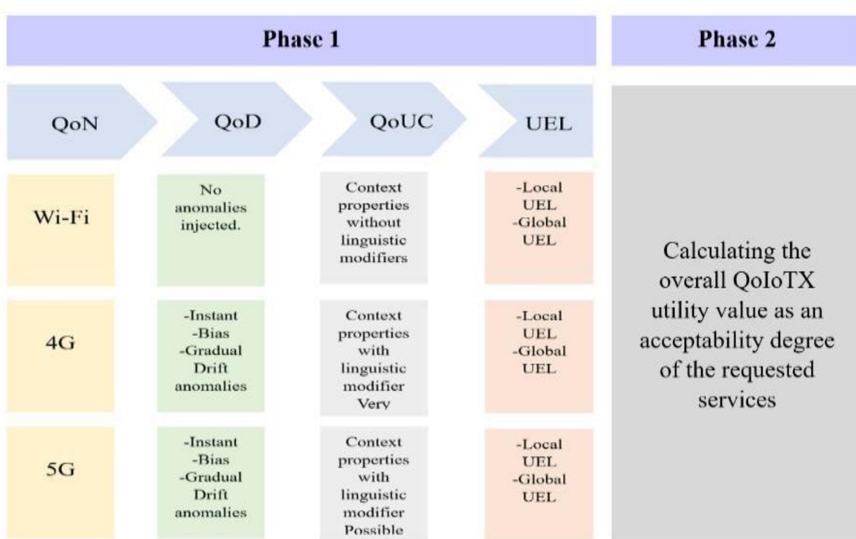


Fig 7 The Taxonomy of The Evaluation Process

3.3.1. Phase 1: Evaluating each of QoE influencing factors.

a) Quality of Things Experience QoTX

• Evaluating the QoN factor

As the relationship between the objective network quality and the end-users' quality perception has been explored and proven in the literature, evaluating the typical QoS metrics such as throughput, delay, jitter, and packet loss is essential when the quality of provided services is considered. From these quantitative metrics, throughput emerges as the most important one in affecting the end-users' perception. It directly influences the performance of the provided services, therefore, their quality of experience.

The active tests are performed with the iperf3 network testing tool, a free, cross-platform and commonly used tool for network performance measurement and testing, by periodically streaming a bulk of packets to achieve the maximum available throughput with time intervals of 10 seconds with zero silence in between, during the services requests. Using the utility function equation 2, and network throughput statistics in table 1, the overall network reliability is evaluated for each service request. These statistics are collected with an active test during services requests; thus, their response time is not separate from request's response time.

Table 1 Available Network Throughput Collected via Active Testing During Services Requests.

Network type	Services	Mean	STD	Min	Max
Wi-fi (Gbps)	Transportation services	4.45	2.06	1.94	8.31
	Traffic detection services	4.11	1.64	2.46	7.52
	Activity services	7.40	1.73	5.11	10.8
	Distance services	6.9	1.80	4.9	8.40
	Street monitoring services	4.45	1.82	2.13	7.59
4G (Gbps)	Transportation services	3.77	1.64	2.22	6.72
	Traffic detection services	3.68	1.87	1.96	7.99
	Activity services	3.04	1.3	1.87	6.6
	Distance services	4.41	2.33	2.1	8.81
	Street monitoring services	3.61	1.67	1.95	6.51
5G (Gbps)	Transportation services	3.72	2.02	1.56	7.5
	Traffic detection services	4.03	1.71	2.12	6.87
	Activity services	3.72	1.78	1.76	8.37
	Distance services	3.46	1.49	1.98	6.75
	Street monitoring services	3.42	1.54	1.76	6.29

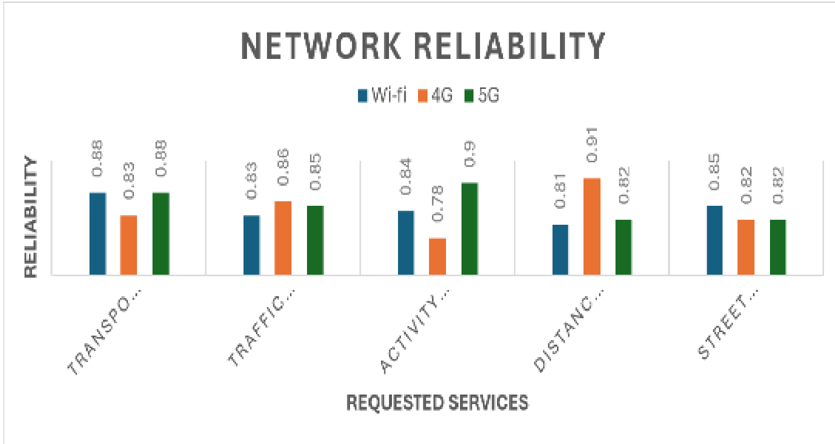


Fig 8. Utility Function Values (Network Reliability Per Each Service Request

As shown in figure 8, there is a diversity in the computed network reliability values with the different network types that have been tested during the request time. However, there is a convergence in these values which indicates a performance similarity between tested networks with more stability in the 5G network.

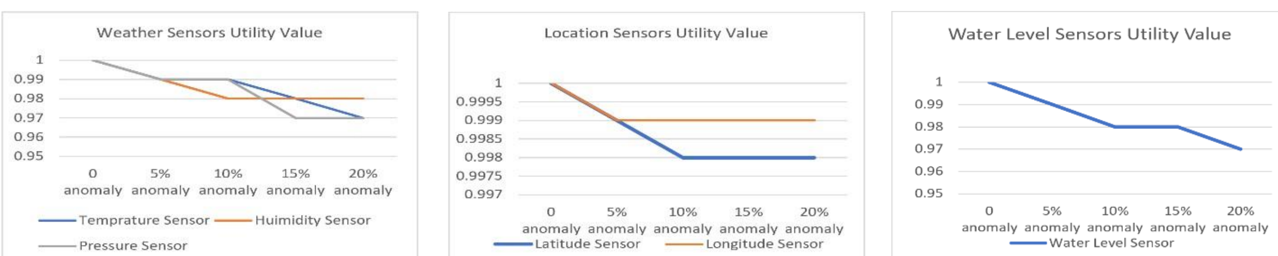
• **Evaluating the QoD factor**

To investigate the potential quality degradation of sensed data, three different types of anomalous sensors behaviour, that can be generated from both sensors faults and injection attackers, are considered: instant anomaly type which is simulated as a Gaussian random variable. Bias type is simulated by adding a temporarily offset to the observation, and gradual drift which is simulated by linearly adding values in increasing or decreasing order to the base value [14 – 15, 31].

Datasets for this work are obtained through simulating three different weather sensors: temperature, humidity, and pressure, and two location sensors: latitude, and longitude. The synthetic data is generated with approximately five hours of sensing processes (collected every second). The simulation tool used to generate the data is the IoT- Data-Simulator, a tool that allows to simulate the IoT devices' data with significant flexibility[31]. Since there are no publically available datasets that include anomalous behaviour in sensor measurements either due to attacks or machine faults, data is injected with three synthetic anomaly types including instant, bias and gradual drift. The anomalies are injected supposing that precisely a kind of anomaly is likely to occur to one of the sensors each time epoch. These anomalies are added to the sensor's base value, i.e., the original sensor readings. Various datasets were generated each with a specific type of anomaly in a specific sensor where the incidence rate of anomaly is set to be 5%,10%, 15%, and 20% respectively. Using the utility function eq. 3, and sensors' data statistics in table 2, the overall accuracy is evaluated for each sensor's data.

Table2. Sensor-related Data as a Part of the QoD Factor evaluation

Sensor Type	Sensor name	Anomaly type	Magnitude/ Duration	%	Min	Max	Std	U(x) value
Weather data	Temperature (Celsius)	Gradual Drift	None	0	29	44	.290	1
			Base+ L(0,1), d=20	5%	29	45	.271	.997
			Base+ L(0,1), d=20	10%	29	47	.242	.994
			Base+ L(0,1), d=20	15%	29	52	.204	.984
			Base+ L(0,1), d=20	20%	29	61	.178	.976
	Humidity (Percentage)	Bias	None	0	0	95	.292	1
			Base+ U(0,2),d=10	5%	0	97	.286	.998
			Base+ U(0,2),d=10	10%	0	98	.283	.986
			Base+ U(0,2),d=10	15%	0	99	.280	.985
			Base+ U(0,2),d=10	20%	0	101	.277	.984
	Pressure (Bar)	Bias	None	0	500	970	.287	1
			Base+ U(0,2),d=10	5%	500	972	.286	.990
			Base+ U(0,2),d=10	10%	500	972	.286	.990
			Base+ U(0,2),d=10	15%	500	973	.285	.979
			Base+ U(0,2),d=10	20%	500	973	.285	.970
Location data	Latitude 1	Bias	None	0	.008573	37.998	.322	1
			Base+ U(0,2),d=10	5%	.008573	39.73816	.276	.999
			Base+ U(0,2),d=10	10%	.01632	41.39698	.265	.998
			Base+ U(0,2),d=10	15%	.01632	42.48203	.259	.998
			Base+ U(0,2),d=10	20%	.01632	42.89803	.256	.998
	Longitude 1	Instant	None	0	-121.99	92.99424	.301	1
			Base+10+N(0,0.01)	5%	-121.99	92.99428	.288	.999
			Base+10+N(0,0.01)	10%	-121.99	92.99428	.288	.999
			Base+10+N(0,0.01)	15%	-121.99	92.99428	.288	.999
			Base+10+N(0,0.01)	20%	-121.99	92.99428	.288	.999
Water level data	Water level	Instant	None	0	.199	1.122	.138	1
			Base +2+N(0,0.01)	5%	.170	1.122	.134	.990
			Base +2+N(0,0.01)	10%	.168	1.122	.133	.987
			Base +2+N(0,0.01)	15%	.163	1.122	.133	.980
			Base +2+N(0,0.01)	20%	.160	1.122	.123	.970



a) Weather Metric Utility Values   b) Location Metric Utility Values   c) Water Level Metric Utility Values

Fig 9. Single-attribute Utility Functions Per QoD Metrics for Data Accuracy

We utilize Eq. 3 in combination with the sensor-related data from Table 2 to build up Single Attribute Utility Functions SAUFs. Then, the goal is to aggregate these SAUFs in Eq. 4 in order to measure accuracy of related data. Figure 9 shows the SAUF Per QoD Metrics (sensor type).

The additive Multi Attribute Utility Function MAUF in the form of Eq.4 is used to evaluate the overall accuracy of each sensor type. As this equation is a linear weighted sum of multiple SAUF, the balanced weight distribution is used. In this technique, equal weights across all the metrics were assigned. This approach can be used when it is difficult to establish a sense of priority among different metrics, thus, all metrics are treated equally, and [32]. In order to maintain an equal distribution of weights to metrics ratio, weights values are specified based upon the number of metrics involved. The summation of all constant weights should add up to a maximum value of 1 i.e., each individual weight must be normalized in the (0, 1) range. Therefore:

$$U\ (Sensor\ Type) = w_1 * U\ (Sensor_1) + w_2 * U\ (Sensor_2) + w_3 * U\ (Sensor_3) + \ldots + wi * U\ (Sensor_i)$$

$$\text{Where} \quad w_1 + w_2 + \ldots + w_i = 1$$

Table 3. The overall Accuracy of Sensed Data

Sensor Type	# of metrics	Weight value	0% anomaly	5% anomaly	10% anomaly	15% anomaly	20% anomaly
Weather	3	.33	1	.96	.96	.96	.96
Location 1	2	.5	1	.98	.98	.98	.98
Location 2	2	.5	1	.98	.98	.98	.98
Water level	1	1	1	.99	.98	.98	.97

Table 3 indicates the calculated overall accuracy of the sensed data using utility function equation. It is worth noting that even in the injection with incidence different rate of anomaly, i.e., 5%,10%, 15%, and 20%, the resulted values are still convergent with no dramatical changes from original values. This is because the anomalies fall into the normal distribution of the base values, thus, there is no extreme changes from the normal values.

- **Evaluating the QoUC factor**

Context information can effectively enhance services and applications usability since it allows to be adopted to the surrounding changing environment. Often, users want to use their devices to access data and request services upon their context related information such as location, time, environment, events, actions, etc. They use linguistic adverbs and adjectives to describe what they need. For example, they can be interested in finding "the closest restaurant to their workplace". Fuzzy and rough theories are utilized to tackle this issue through reasoning with non-crisp ontology concepts. This vagueness and impreciseness can be handled by defining appropriate linguistic variables and modifiers through which truth degrees are identified depending on a specific level of certainty. According to the targeted domain, the intended modeled information is focused on the 5Ws questions (who, when, what, where and why). Who is the user? What is he doing? When has it happened? Where is the location? And why this would be happened? The following are the derived context information of the identified scenarios attached with the Probability of Correctness PrC values.

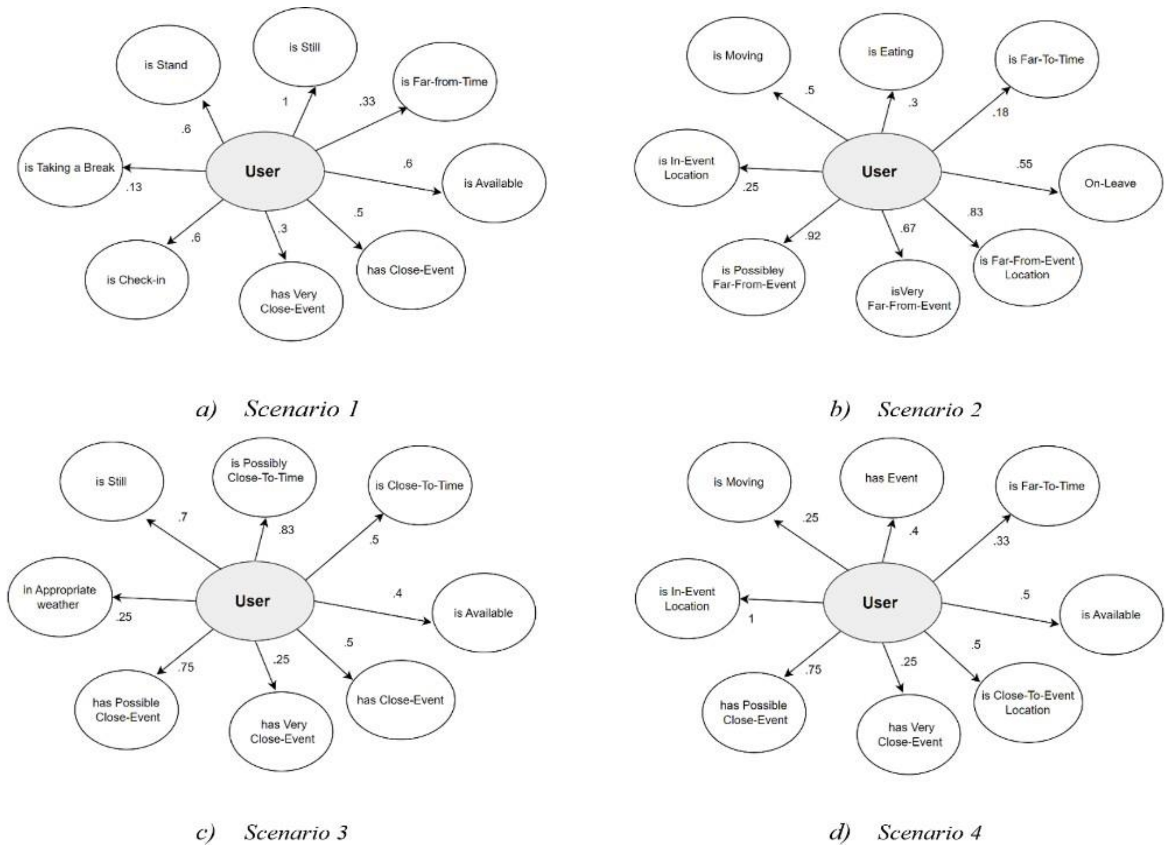


Fig 10: Four Different Scenarios with Different Derived Context Information

The relationships depicted as arrows, in the developed scenarios represent the user's context with attached numbers indicate confidence levels (i.e., PrC) which refer to correctness of the given contextual information. Figure 10 shows four different scenarios for four different users. As depicted in figure 10-a, the first scenario is for a traveler in the airport looking for some services such as distance services, food services, payment services, etc. using the fuzzy rough ontology, his current contextual information is derived with a level of certainty (confidence) represents the probability of correctness of such information. Here, as a mobility status, we can see that the user is still with 1 confidence level, i.e., the user is 100% still, not moving. The figure also shows that his status is available with .5 confidence level. He has a close event (a flight) in his calendar that with .5 confidence level and it's time is far from his current time with .33 certainty. We also know that he has already checked in and is taking a break now with .6 and .13 confidence levels respectively. In various cases of real-life scenarios, people need to express their everyday requirements using linguistic hedges (also called modifiers) such as very, possibly to impose emphasizes on them. These hedges can be considered as special expressions by which the degree of membership of fuzzy datatype could be modified. Using these modifiers, context dependent characteristics could be adequately identified, thus, express users' preferences more accurately through adjusting the confidence level of the inferred context. It is noted that in this scenario, these hedges are used to emphasize, thus, alter the confidence level of some context properties. For instance, we know that this user has a close event with .5 certainty. Using the "Very" modifier, this confidence level is altered to be just .3. Using Eq. 5, context attributes are mathematically mapped to the overall QoUC probability of correctness value. PrC(ai) denotes the probability of correctness, i.e., confidence level of context attribute ai, and wi indicates the wight by which the priority of each attribute is identified. Here, the balanced weight distribution is used. In this technique, we assign equal weights across all the metrics and the summation of all constant weights in the equation should add up to a maximum value of 1. The second scenario in figure 10-b is for a visitor in a restaurant looking for a taxi service, or a transportation service, and/or traffic detection services. This user has an upcoming event retrieved from his calendar in a specific location. He is moving with .5 confidence level, his status is on-leave with .55 certainty, his upcoming event is far from his current time with .18 confidence, and it is known that he is eating with just .3 certainty. Here, the derived confidence levels are modified by using linguistic hedges with the “event location” property. As depicted, the properties: “in-event- location, far-from-event-location, very-far-from-event-location, possibly-far-from-event-location” have .25, .83, .67, .92 confidence levels respectively. Again, the derived confidence levels are modified by using linguistic hedges with the “has-event” property. Table 4 shows the calculated QoUC of different context properties of these presented scenarios.

Table 4. The Calculated QoUC of Different Context Properties of the presented scenarios

Scenario #	Context properties	Weight value	Estimated QoUC	Scenario #	Context properties	Weight value	Estimated QoUC
Scenrio1	Still/ available/ close-event/ far- from-time/ checked-in	.2	.61	Scenrio3	Still/ available/ close-to-time/ close-event/ appropriate-weather	.2	.47
	Still/ available/ very-close-event/ far- from-time/ checked-in	.2	.56		Still/ available/ possibly-close-to-time/ close-event/ appropriate-weather	.2	.53
	Still/ available/ close-event/ far- from-time/ checked-in/take-break	.17	.53		Still/ available/ close-to-time/ very-close-event/ appropriate-weather	.2	.42
	Still/ available/ very-close-event/ far- from-time/ checked-in/stand	.17	.58		Still/ available/ possibly-close-to-time/ possibly-close-event/ appropriate-weather	.2	.58
Scenrio2	Moving/ on-leave/ far-from-time/ eating/ in-event-location	.2	.35	Scenrio4	Moving/ available/ has-event/ Far-to-time/ in-event-location	.2	.49
	Moving/ on-leave/ far-from-time/ eating/ far-event-location	.2	.47		Moving/ available/ has-event/ Far-to-time/ close-to-event-location	.2	.39
	Moving/ on-leave/ far-from-time/ eating/ very-far-event-location	.2	.44		Moving/ available/ very-close-event/ Far-to-time/ in-event-location	.2	.46
	Moving/ on-leave/ far-from-time/ eating/ possibly-far-event-location	.2	.49		Moving/ available/ possibly-close-event / Far-to-time/ close-to-event-location	.2	.46

b) Quality of Human Experience QoHX

The quality of IoT application/service can be efficiently inferred through monitoring User Engagement Level UEL. The subjective human factors QoHX such as usage patterns including No. of times users request the services are evaluated by categorizing the interactions that performed with the applications/service. These interactions are aggregated according to usage patterns to quantify the overall user engagement. Two usage metrics are extracted from the logs data: Frequency of use and Comprehensiveness of use.

Each experiment (i.e., service request) is replicated several times (4,5,6, and 7) to build the service’s access log file in Table 4. The Calculated QoUC of Different Context Properties of the presented scenarios which each row represents a session for a specific user with information related to user’s ID, service name, frequency of use, comprehensiveness of use, and response time for each request. To model the relationship between these two factors and the overall UEL, Multiple linear regression (MLR) is utilized. For each user in the service log file, the frequency of use and comprehensiveness of use are calculated as local and global usage patterns. If the user has not requested the service before, i.e., the local usage pattern is 0, the UEL will be considered as the global usage pattern in this case.

Table 5. User 1 Calculated UEL for Different Service Type Requests

Service Type	Service Name	Calculated UEL	Service Type	Service Name	Calculated UEL
Transportation services	Taxi location service	.43	Street monitoring services	Street camera service	.60
	Taxi availability service	.39		Street water level service	.37
	Bike availability service	.25		Street temperature service	.43
	Bus availability service	.37		Street dashboard service	.33
Activity services	Activity search service	.41	Traffic detection services	Traffic detection service	.45
				Get traffic information service	.34
Distance services	Get DistanceBetweenLocations service	.42	Distance services	Get DistanceInMiles service	.35

Table 5 shows user's calculated UEL values for different service type requests. As seen, users in some cases prefer some services to others. For example, in the transportation services, it is clearly that the "Taxi location service." Is the most preferable service by this user while the "Bike availability service." is the least preferable one with just .25 as a UEL value. In the street public services, we can see that the user is always requesting the camera service which is clearly reflected in the significant difference between its UEL value comparing with other values for services in the same type. It is worth noting that as the MLR model is utilized with two different parameters represent the frequency of use and comprehensiveness of use, we can eliminate the frequency of use part by make its coefficient equal to zero to examine the preferences of other users that represented by the "comprehensiveness of use" parameter. This allows us to rank the requested services according to users' preferences. For example, the transportation services ranked according to the global usage pattern are .36, .36, .35, and .23 for taxi location, taxi availability, bus availability, and bike availability respectively. These results demonstrate a significant convergence between taxi services and bus service as preferable services for other users. Distance services will be ranked as .36, and .35 for Get DistanceBetweenLocations service and Get DistanceInMiles service respectively which indicates a convergence that does not appear when these services ranked considering the local usage pattern parameter, i.e., the user's frequency of use.

3.3.2. Phase 2: Evaluating the overall QoIoTX utility values as an acceptability degree

Requests are sent using a MQTT communication broker through Wi-Fi, 4G, and 5G networks. Once the user request arrives for searching the services by keyword, the service request parser in the service matching module parses the request and sends the extracted details to the search component. During the experiments, the laptop is utilized as a consumer (localhost) to send requests to the services' gateway which is the localhost as well. The performance of the proposed framework is assessed by interpreting the problem of quantifying each of the QoE influencing factors, calculating the overall QoIoTX value as an optimization problem such that the total utility value of the service has to be maximized as an acceptability degree, and ranking the requested service accordingly.

After evaluating each of the influencing factors in phase1, the overall QoIoTX utility values are calculated to be mapped into a bipolar interval scale to determine the user's overall Acceptability degree. The evaluation process in phase 2 starts by changing one influencing factor at a time with keeping the others without changes to examine to what extent each of these factors affect the QoE of different IoT services. Table 6 illustrates the services requested by the user using different networks, different data accuracy, and different user's context status. The last column represents the acceptability degree in which the value of QoIoTX is mapped into a bipolar interval scale (please note that due to space limit, the table consists only four service domains).

Table 6 The QoIoTX Utility Values, and Their Mapped Acceptability Degrees of Requested Services.

Influencing factor	QoN		QoD		QoUC		UEL		QoIoTX utility value	Acceptability degree
Transportation services										
QoN	Wi-fi	.88	20% anomalies .98		Scenario 1 .56		Taxi location service	.43	.71	Very Good
									.70	Very Good
									.71	Very Good
							Taxi availability service	.39	.70	Very Good
	4G	.83							.69	Very Good
									.70	Very Good
							Bike availability service	.25	.66	Very Good
									.65	Very Good
									.66	Very Good
	5G	.88					Bus availability service	.37	.69	Very Good
									.68	Very Good
									.69	Very Good
QoD	4G .83		0% anomalies	1	Scenario 1 .56		Taxi location service	.43	.70	Very Good
									.70	Very Good
							Taxi availability service	.39	.69	Very Good
									.69	Very Good
			20% anomalies	.98			Bike availability service	.25	.66	Very Good
									.65	Very Good
							Bus availability service	.37	.69	Very Good
									.68	Very Good
QoUC	4G .83		20% anomalies .98		Scenario 1	.56	Taxi location service	.43	.70	Very Good
									.63	Good
									.67	Very Good
									.65	Very Good
					Scenario 2	.35	Taxi availability service	.39	.69	Very Good
									.63	Good
									.66	Very Good
									.64	Very Good
					Scenario 3	.47	Bike availability service	.25	.65	Very Good
									.60	Good
									.63	Good
									.61	Good
					Scenario 4	.39	Bus availability service	.37	.68	Very Good
									.63	Good
									.66	Very Good
									.64	Very Good

Influencing factor	QoN	QoD	QoUC	UEL	QoIoTX utility value	Acceptability degree
Traffic detection services						
QoN	Wi-fi .83	20% anomalies .98	Scenario 2 .35	Traffic detection service .45	.65	Very Good
					.66	Very Good
					.65	Very Good
	4G .86			Get traffic information service .34	.62	Good
	5G .85				.63	Good
					.63	Good
QoD	4G .86	0% anomalies 1	Scenario 2 .35	Traffic detection service .45	.66	Very Good
					.66	Very Good
		20% anomalies .98		Get traffic information service .34	.63	Good
					.63	Good
QoUC	4G .86	20% anomalies .98	Scenario1 .61	Traffic detection service .45	.72	Very Good
					.66	Very Good
			Scenario2 .35		.71	Very Good
					.68	Very Good
			Scenario3 .58	Get traffic information service .34	.69	Very Good
					.63	Good
			Scenario4 .46		.69	Very Good
					.66	Very Good

Influencing factor	QoN	QoD	QoUC	UEL	QoIoTX utility value	Acceptability degree
Distance calculation services						
QoN	Wi-fi .81	20% anomalies .98	Scenario 4 .49	Get DistanceBetweenLocations .42	.67	Very Good
					.70	Very Good
					.67	Very Good
	4G .91			Get DistanceInMiles service .35	.65	Very Good
	5G .82				.68	Very Good
					.66	Very Good
QoD	4G .91	0% anomalies 1	Scenario 4 .49	Get DistanceBetweenLocations .42	.70	Very Good
					.70	Very Good
		20% anomalies .98		Get DistanceInMiles service .35	.68	Very Good
					.68	Very Good
QoUC	4G .91	20% anomalies .98	Scenario1 .61	Get DistanceBetweenLocations .42	.73	Very Good
					.66	Very Good
			Scenario2 .35		.68	Very Good
					.70	Very Good
			Scenario3 .42	Get DistanceInMiles service .35	.71	Very Good
					.64	Very Good
			Scenario4 .49		.66	Very Good
					.68	Very Good

Influencing factor	QoN		QoD		QoUC		UEL		QoIoTX utility value	Acceptability degree
Street monitoring services										
QoN	Wi-fi	.85	20% anomalies	.96	Scenario 2	.35	Street camera service	.60	.69	Very Good
									.68	Very Good
									.68	Very Good
							Street water level service	.37	.63	Good
	4G	.84							.63	Good
									.62	Good
							Street temp service	.43	.64	Very Good
									.64	Very Good
	5G	.82							.64	Very Good
							Street dashboard service	.33	.62	Good
									.62	Good
									.61	Good
QoD	4G	.84	0% anomalies	1	Scenario 2	.35	Street camera service	.60	.69	Very Good
									.68	Very Good
							Street water level service	.37	.64	Very Good
									.63	Good
			20% anomalies	.96			Street temp service	.43	.65	Very Good
									.64	Very Good
							Street dashboard service	.33	.63	Good
									.62	Good
QoUC	4G	.84	20% anomalies	.96	Scenario 1	.56	Street camera service	.60	.74	Very Good
									.68	Very Good
									.71	Very Good
									.69	Very Good
					Scenario 2	.35	Street water level service	.37	.68	Very Good
									.63	Good
									.66	Very Good
									.63	Good
					Scenario 3	.47	Street temp service	.43	.69	Very Good
									.64	Very Good
									.67	Very Good
									.65	Very Good
					Scenario 4	.39	Street dashboard service	.33	.67	Very Good
									.62	Good
									.65	Very Good
									.63	Good

In order to investigate the impact of each of evaluation factors, we start to change one factor to be considered as determinant factor with no changes in other factors to examine how this factor can significantly affect the overall IoT service's QoE. First, we have three different types of networks: wi-fi, 4G, and 5G, each with different utility value represents the evaluation of its reliability during the services request process. As depicted in table 6, with each network type, when each of other influencing factors, i.e., QoD (20% anomalies) and QoUC are kept without changes, results demonstrate that the performance of the underlying network during the service discovery process can significantly affect the overall QoE of the requested services. This effect is clearly reflected with the overall evaluation values of the distance services, and transportation services. As shown, when the network reliability is .76, the overall QoIoTX utility value is .69 which is less than the estimated values when the reliability is greater than .76. Another example of such an effect can be noticed in the distance services case. The QoIoTX utility value significantly dropped from .70 to .67 when the network reliability changed from .91 to .81. It can be noticed that the highest QoIoTX utility value is achieved with the 4G network. This can be explained due to the coverage diversity between the selected networks (the coverage of 4G network is greater than 5G within the city). These results indicate that the inclusion of the network evaluation metric (network reliability) in the service QoE estimation can improve the discovery efficiency in IoT service environment.

The second quality metric to examine is the QoD. To investigate the effect of this metric on the overall QoE, we select the utility values of two anomaly injection percentage: 0%, i.e., no anomalies injected, and 20% anomalies injected. The rest two factors (QoN and QoUC) are fixed, with .87 utility value of the 4G network reliability (the best performance) and .61 as probability of correctness from scenario 1 context evaluation, with all calculation cases. As illustrated in table 6, it can be noticed that the values of the computed QoIoTX are different when the values of the estimated QoD are changed even though, as previously mentioned, the resulted values are still convergent with no dramatical changes due to the fact that the anomalies fall into the normal distribution of the base values, thus, there is no extreme changes from the normal base values. These results indicate that the inclusion of the quality of data metric in the service QoE estimation can improve the discovery efficiency in IoT service environment.

The third metric is the QoUC metric in which the user's context probability of correctness is changed according to the different two scenarios provided in the QoUC evaluation section in phase 1. Table 6 confirmed the claim that the user's context influences the service acceptability degree evaluation. As shown, the higher the probability correctness value of the context properties, the better QoE estimation which emphasizes the significant role of this factor in service evaluation process. For example, in the "Get traffic information service" from traffic detection services, the QoIoTX value of the service has been changed from .69 "Very Good" to be just .63 "Good" affected by the change of the probability correctness value of the context properties from.58 to .35 and with "Taxi location" service from transportation services when the value changed from .56 to .35. This indicates that the utilization of the fuzzy rough ontologies in capturing user's current context can enhance the evaluation of the QoUC factor, thus, improve the discovery efficiency in IoT service environment.

A further novel finding is that the second part of the eq. 1, i.e., the Quality of Human Experience QoHX part that represented by the UEL evaluation has a significant impact on the calculation results. The present results demonstrate this effect clearly through the changed QoIoTX utility values when the UEL value is changed. For instance, in the traffic detection services, the user has different UELs for the two services which indicates a different engagement level between them. This difference impacted the acceptability degree to be "Very Good" for the greater UEL value.45) and "Good" for the smaller UEL .34. This also appeared with the "Bike availability service" in transportation services when the UEL value dropped to .25, the QoIoTX utility value dramatically dropped to be .66 accordingly. This emphasized that increasing the UEL value positively changes the overall estimated QoIoTX value which indicates that examine whether the inclusion of the user's usage patterns of a service can positively affect the QoE of that service. Figure 11 shows different requested services ranked according to the calculated QoIoTX utility and UEL Values.

Fig 11. Different Requested Services Ranked According to The Calculated QoIoTX Utility Values and UEL

4. Related works

QoE is a subjective factor that reflects the feeling users have when they interact with services and applications, thus, it can be determined by the degree of acceptability a service/application is gained when end users use this service/application. The European Network Qualinet community defines QoE influence factor as “any characteristic of a user, system, service, application, or context whose actual state or setting may have influence on the Quality of Experience for the user" [5]. The vast majority of existing QoE works mainly focus on services/applications in which humans have a primary role through providing their feedback regarding the performance of the intended service and/or application neglecting other services where humans are not involved in the loop.

QoE definitions are categorized according to models utilized to evaluate the quality of a given service into subjective QoE evaluation metrics and hybrid metrics in which both subjective and objective factors are integrated. Often, subjective metrics consider parameters related to human perception including satisfaction, enjoyment, feelings, expectations, motivation, etc. In contrast, objective metrics are quantitative measures that objectively evaluate the performance of an application/service.

Yang et al. [35] classified the QoE influencing factors into: objective and subjective factors. Objective factors include system parameters related to network, application, and service layers, and context parameters such as physical and social context. Subjective influencing factors include parameters related to user’s mental state, profile, motivation, and expectation. Although objective metrics have a fundamental role in quality evaluation process, authors emphasized that subjective metrics are important to represent the actual user’s quality perception. Table 7 illustrates the QoE influencing factors classified to subjective and objective categories.

Table 7: QoE Influencing Factors Classification

Objective factors	System factors	Network layer	Delay, bandwidth, jitter, packet loss.
		Application layer	Frame rate, codec type, resolution.
		Service layer	Application level, content type, quality assurance.
	Context factors	Physical context	Location, mobility.
		Social context	Sharing, solitary.
		Temporal/task context	Time, battery consumption.
Subjective factors	Human factors	User profile	Age, sex, experience, education level.
		Mental state	User preferences, enjoyment, expectation, motivation
		Expectation	
		Motivation	

As they mainly focus on measuring the quality of service/application (particularly multimedia services) considering users being involved in the loop and neglecting some other significant factors related to machine experience, wherein, users are not always involved in the process, subjective measures may fail to evaluate the actual performance of the intended service/application [36]. Despite the fact that subjective measures are the most quality evaluation tools utilized to grasp user's feedback regarding a specific service, recently, the efficiency of such techniques such as MOS, differential MOS and the ACR-HR [38 – 40] is widely questioned by researchers. For example, in IoT environment, there are tremendous number of automatic services/applications that don't ask for user's feedback as their users are not always humans, i.e., they are utilized to actuate other services. In such cases, subjective metrics may not be the appropriate tools to evaluate the performance of these services. Therefore, there is an argent demand to identify some other metrics by which the overall perceived quality is evaluated.

According to Fizza et al. [40] in IoT applications, it is difficult to assess their performance to check whether they meet the specified Key Performance Indicator KPIs and quality specifications. They stated several reasons to justify such difficulty. First, in this type of application, human feedback, through which the QoE of the application can be evaluated, is not available. Second, outputs of these applications are not simple actuations to apply specific settings, instead, they are resulted by integrating multiple processes including using sensors for collecting data, processing, and analyzing the collected data using data analytics tools, and making decisions accordingly. Evaluating how the quality of the final results are affected by this integration is a challenging task. In addition, the introduction of edge computing paradigm added additional complexities as the processes of data analysis and storage are carried out at the edge of the network without the requirement of transferring them to a distant center. This distribution nature requires continuous quality assessment.

Mitra et al. [41] and Minovski et al. [43,44] argued the fact that in ecosystems such as IoT system, the output of an IoT application can be utilized by other IoT application instead of a human, thus, user's feedback is not obtainable. Therefore, additional objective metrics (utilizing mathematical/ statistical models) to consider machine to machine interaction quality evaluation are urgently required to be combined with the trivial subjective metrics. According to end user orientation, Floris et al. [44] classified IoT applications into user-oriented applications in which humans are considered as the primary beneficiaries, thus, have an essential role in quality assessment process. on the other hand, system-oriented applications, data is autonomously collected, processed, and managed to perform the required task. However, authors assert that user's participation should be considered in both types of applications as they are primarily managing the smart controllers.

Evaluating the QoE in IoT environment is considered a relatively new research area, therefore, there is still no consensus on well-defined measures to evaluate the perceived quality of a service/ application. However, there are several remarkable works attempting to develop QoE evaluation models and integrate the traditional assessment techniques into the IoT paradigm. Pal et al. [46,47] addressed the QoE evaluation in smart wearable applications domain through modeling the relationship between user's experience and quality perception. The QoE is modeled as a function of QoD and Quality of Information QoI, i.e. the quality of the information related to user's requirements at a specific time, place and social settings. The authors defined three essential factors that are directly associated with quality evaluation of this type of applications. These factors include the quality of embedded sensors used to collect data, the algorithms utilized to analyze these data, and the way they are presented to end users, i.e., application characteristics. In order to build the mathematical model, a subjective experiment is conducted in a free-living environment. The accuracy of the presented mathematical model is tested by comparing results obtained from the model with the subjective experiment results. Despite of their achieved R2 and adjusted R2 accuracy measures values (0.65 and 0.63), and the fact that their work considered the QoI as a user-centric factor, authors neglected the significance of the technology-centric metrics such as QoS which has an important impact in IoT applications.

Floris et al. [44] developed a layered QoE model in which multiple influential factors are integrated into to evaluate the overall QoE in multimedia IoT applications. Each layer models the quality associated with a specific IoT layer and can be integrated with both upper and lower layers. This feature allows to build a model in which the output of a specific layer can be interpreted and utilized by a higher layer. The model consists of five layers: physical layer, network layer, virtualization layer, combination layer and application layer. To test the proposed model, two use cases were experimented with comprehensive analysis: a smart surveillance application and multimedia vehicle application. Three different parameters were subjectively assessed by 24 participants the quality of videos, the synchronization process and the accuracy of data related to the vehicle. Although some significant influencing factors were considered such as the quality of data (data accuracy), the work mainly focused on IoT multimedia applications. Table 8 summarizes some of QoE evaluation works regarding their different approaches, implementation, characteristics and limitations.

Table 8 Summary of Some Existing QoE Evaluation Works in IoT Environment.

Author	Approach	Limitations
Mitra et al. [47]	Context-aware framework to measure QoE on a single scale.	They used only two influencing factors: QoS in terms of delay, packet loss, and location as a context attribute
Mitra et al. [48]	Bayesian networks (BNs) and utility theory are incorporated for quality of experience (QoE) measurement and prediction.	They used only QoS factors such as jitter, delay, packet loss and location context attribute in addition to the Mean Opinion Score MOS to determine user satisfaction.
Mitra et al. [49]	A context-aware approach for quality of experience (QoE) modeling, reasoning based upon Context Spaces Model (CSM) and Bayesian networks.	They used only QoS factors such as delay, packet loss and location context attribute.
Mitra et al. [41]	A decision-theoretic approach CaQoEM to model, measure and predict the QoE.	They used only QoS factors such as jitter, delay, packet loss and location context attribute in addition to the Mean Opinion Score MOS to determine user satisfaction.
Floris and Atzori [44]	A layered-QoE framework to evaluate the quality of a multimedia IoT service.	Authors do not provide methodological steps on measuring QoD, they use an abstracted version of it in combination with QoS to map to subjective QoE scores. In addition, they provide no indications on how the models could cover other IoT services except multimedia.
Pal et al. [46]	A mathematical relationship between human experience and quality perception in the smart-wearable domain.	Their mathematical model includes only two influencing factors: Quality of Data QoD, and Quality of Information QoI, neglecting other significant factors such as QoS.
Minovski et al. [43]	modeling the relationship between humans and intelligent machines through quantifying the perspectives of intelligent machines with other objective metrics.	Their model includes only two influencing factors: Quality of Data QoD, and Quality of Network QoN.

The existing QoE literature reveals that their limitations mainly fall into several issues. First, there is a lack of generic architecture or framework to identify, measure, and evaluate the quality of the autonomic IoT service/application. Second, Still, most of the work are extensively utilized within multimedia domain to fulfill the network quality requirements through Quality-of-Service QoS evaluation metrics including network delay, jitter, packet drops, and bandwidth. These parameters do not reflect the actual service quality perception but the media and the network underlying the service. Third, in the conventional QoE metrics, services/application are subjectively measured using metrics such as Mean Opinion Score MOS, Standard deviation of Opinion Scores

SOS, and Acceptability that reflect the qualitative opinion of end users including satisfaction, happiness, feelings, expectations, desires. Such metrics primarily focus on services/applications in which experiments are conducted to involve humans to provide their feedback regarding the performance of the intended service and/or application. These experiments could be expensive and time consuming. Fourth, despite the fact that some existing works considered other evaluation metrics such as QoD, QoI and QoC, they did not provide any methodological steps or holistic approach to measure them, they provide only an abstracted version of them. Our proposed framework deviated from the conventional QoE evaluation paradigm and went beyond the legacy QoS techniques. This could be achieved through addressing the evaluation of QoE in IoT services from two distinct but often complementary perspectives: objective, and subjective quality assessment. It stands out by considering various objective and subjective quality influencing factors including QoD, QoN, QoUC, and service usage pattern data in a comprehensive manner which has yet to be fully investigated in the illustrated studies. It addressed the issue of the fact that each of such identified factors is measured on a different scale and may involve different units of measurement. In addition, other novel alternative approach was considered to evaluate the IoT services/applications subjectively rather than using the classical old approaches that do not adequate with the massive current and rapidly evolving services and applications, and with the dynamicity nature of their IoT environment.

Table 9 Comparative Analysis of Some Existing QoE Evaluation Works VS The Proposed Work

Research paper	Application domain	QoE metrics evaluated				Defining QoE for IoT	Validated
		QoD	QoN	QoUC	Service usage pattern		
Floris and Atzori [44]	Multimedia	Partially	Partially	Partially	No	No	No
Huang et al. [50]	Multimedia	No	✓	No	No	No	✓
Karaadi et al.[51]	Multimedia	No	✓	No	No	No	No
Minovski [43]	General	✓	✓	No	No	✓	No
Shin [52]	Wearable	No	✓	No	No	No	✓
Suryanegara et al. [37]	Smart cities	No	No	No	No	✓	✓
Wu et al. [9]	General	✓	No	✓	No	No	No
Pal et al. [46]	Wearable	✓	No	No	No	No	✓
Mitra et al. [41]	General	No	✓	✓	No	No	✓
QoIoTX framework	General	✓	✓	✓	✓	✓	✓

Table 9 summarizes some presented QoE evaluation works and attempt to compare those tools with the proposed work regarding their application domain, QoE metrics evaluated, whether defining the QoE in IoT and evaluating the proposed work or not.

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