Apples vs. Oranges: The QoE Scenario in Consumer IoT Services

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***Abstract*—IoT services are being deployed in a variety of contexts ranging from smart-homes, smart-cities, smart-healthcare, smart-transportation to smart-industry. Traditionally, Quality of Experience (QoE) that typically measures the end-users' satisfaction level with a particular service has been associated with multimedia services. In this article, we present how IoT services are unique, and why the traditional way of QoE evaluation is not a good approach in this changing scenario. There must be a paradigm shift from a user-centric approach as currently followed, to an approach that combines human to machine (H2M), and machine to machine (M2M) communications. We present a conceptual approach towards such a shift. For the consumer electronics (CE) community this article sheds light on the future research directions in evaluating the QoE for various consumer IoT services.**

Keywords—Artificial intelligence, Consumer IoT, Human-to-machine, Machine-to-machine, Quality of Experience

I. INTRODUCTION

In a very short period, modern technologies like edge computing, fog computing, and IoT have radically changed the way people live by enabling digital transformation. **Fig. 1** shows a typical present-day connected environment, where IoT has its presence in a variety of usage contexts, ranging from smart-homes, smart-transportation, smart-agriculture, smart-health to even smart industries. Since these IoT services are meant for the users, ensuring decent service quality is of utmost importance. Traditionally, such user satisfaction is measured by QoE that is indicative of overall service acceptability, as perceived by the end-users. However, the problem is current QoE approaches are deeply rooted in a multimedia environment [1]. IoT services are not only varied, but have their specialties, and are often symbolized by the 3Cs (connection, computation, and communication) [2]. Traditional QoE evaluation schemes do not consider the aspects of M2M communications, automation, and the autonomous processes on QoE; all of which are highly relevant in the IoT context. The tight integration of humans, machines, and automation create unique challenges that we illustrate with an example. A highly advanced IoT-based flight control system called MCAS (Maneuvering Characteristics Augmentation System) was designed by Boeing and used in

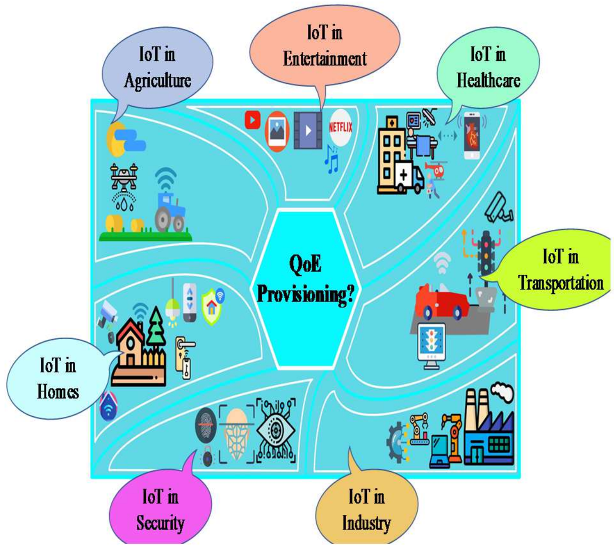

Fig. 1 A Connected IoT Environment in Multiple Domains

their 737 MAX series of aircrafts. This system was supposed to reduce the pilot's workload and improve the aircraft handling capabilities by automating certain procedures. Unfortunately, two Boeing 737 MAX aircrafts crashed soon after takeoff; killing all people on-board, which was attributed to the MCAS system. In both the crashes wrongly sensed data triggered a false high angle-of-attack input, pushing down the aircraft's nose automatically that the pilots could not override. A total lack of H2M interactions, incorrect M2M interactions, and "*surprise automation*" resulted in two fatal air crashes. Therefore, it becomes imperative that interactions and QoE evaluation in an IoT context needs a fresh look beyond the current approaches that are presented in this article.

II. QOE FOR IOT: WHAT IS DIFFERENT?

Current QoE evaluation techniques broadly consider the impact of two different factors: the network and application-layer impairments commonly referred to as the Quality of

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TABLE I. CHALLENGES FACED BY CURRENT STATE-OF-ART QOE EVALUATION STRATEGIES

#	Challenges
1	How can the end user interact or alter the performance of the complex SoS involving various autonomous processes
2	How the physical, network and logical components affect each other in the complex SoS scenario
3	How to evaluate the quality of the SoS and monitor their impact on overall IoT service performance
4	What objective metrics should be used for quality evaluation considering the complexity of SoS
5	How can quality be adjusted in real-time considering the real-time nature of the SOS

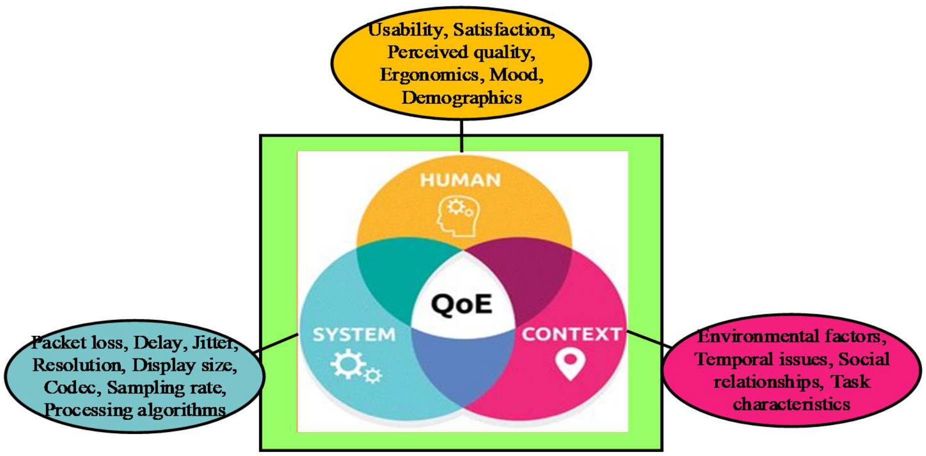

Fig. 2 The Three Traditional QoE Dimensions

Service (QoS) parameters. Packet loss, delay, bandwidth, and jitter are the commonly used network QoS factors, while video resolution, codec type, and device factors (e.g., screen resolution, form factor, etc.) are normally used as application QoS factors [3]. This is in a typical multimedia use-case scenario, from where the concept of QoE originated. Thus, human, system, and context are the three different dimensions that count towards the QoE evaluation as shown in **Fig. 2**.

With reference to the CE context, a few studies have investigated the network aspects of 5G on QoE [4], measured the users' perceptions towards smart-wearables in a healthcare context [5], and even focused on the reliability of the software found in the CE devices [6]. However, the QoE approach in an IoT context is rather fragmented, and still in its infancy [7]. One striking difference between multimedia and IoT services is that the latter integrates heterogeneous functionalities, with the inputs and outputs coming from both humans and machines. Apart from such M2M communications, as mentioned previously IoT systems tend to be autonomous wherein a single decision is taken based on data infusion from multiple sensors that are often inter-dependent. Due to such a high degree of cohesion between the various segments, in case of failures, the effects are often multidimensional. For e.g., IoT systems can fail due to malfunctioning of the IoT hardware/software leading to poor data quality, network failures due to packet loss, delay or jitter, or even problems associated with virtual resources like data processing, and storage. Input and output data coming from both humans and machines has resulted in the creation of an extremely complex system, sometimes referred to as System of Systems (SoS).

Artificial intelligence (AI) is a key enabler of SoS. The presence of AI together with the M2M communications is what makes the IoT context unique. AI tries to make the SoS perform tasks that would otherwise require intelligence if done by a human. In this sense, the machines also perceive an "*experience*", which is arguably different from the human experience (traditional QoE). Recent advancements in explainable AI (XAI) suggest that any action performed by AI is traceable and can be explained by objective data and mathematical models. This means that for the IoT devices that have AI built into them, the perceived quality can be evaluated at run-time using data-driven approaches. We refer to this as the Quality of Systems (QoSys) and define it "*to be an objective parameter just like QoE, but one which measures the quality and performance of the SoS, and the decisions made by those*". Since this is a data-driven approach one key challenge is to identify the data sources and their main components with regards to the SOS. Based on [8], three main data components are identified: physical, logical, and network.

1) *Physical components* are related to the data generated from the hardware or software. It can be measured using fault tolerance, anomaly detection, or physical monitoring.

2) *Network components* are related to QoS focusing on the measurement of the way physical devices and the end-users communicate.

3) *Logical components* are related to the software or hardware controller that houses the IoT hardware for enabling the M2M interactions, and autonomous knowledge creation.

In **Table I** we have attempted to summarize the limitations and challenges faced by the current state-of-art QoE evaluation methodologies in the consumer IoT scenario.

TABLE II. A TAXONOMY OF THE QOE DIMENSIONS IN CONSUMER IOT CONTEXT

Dimension	Metric	Description
(QoE)	Communication	Quality of communication via traditional QoS metrics
	Computation	Quality of resources needed to handle information (e.g cloud)
	Access	Quality of applications presented to the user by offering services
$(QoSys)$	Machine entity	Optimizing the overall operations of the SOS
	Business entity	Providing business goals and services depending on user needs
(QoD)	Accuracy	Collected data must match closely with the requirements
	Truthfulness	Indicative of degree of reliability of the data source
	Completeness	All the required data is present in the data collected by sensors
	Up-to-dateness	Arrival of data on time that assists in decision making
	Precision	Relevancy of data related to what is received from sensors
(QoI)	Timeliness	Timely information for an IoT service (opposite to latency)
	Validity	The synthesized/provided information is true
	Recall	Proportion of relevant information retrieved from a query
	Accuracy	Degree of the accuracy of information to the decision-maker
	Detail	Completeness of the information provided to the decision-maker
(QoC)	Energy efficiency	Overall energy utilization of the IoT system
	Computation efficiency	Computational performance obtained with available resources
	Storage efficiency	Ability to store and manage data within a given storage space

III. QOE FOR IOT: MEASUREMENT STRATEGY

After presenting the challenges of QoE evaluation in the consumer IoT scenario, in this section we outline a taxonomy for the IoT QoE evaluation (QoE_{IoT}). Due to the uniqueness of the IoT context as presented in the previous section, three additional dimensions are considered while evaluating the $QoSys$. These three sub-dimensions are Quality of Data (QoD), Quality of Information (QoI), and Quality of Cost (QoC). **Table II** provides a brief description of the different dimensions and describes what each of these dimensions measure.

As illustrated before, in the traditional scenario QoE is measured from human entities that may involve both subjective and objective approaches. These human entities can be end-users, or even customers from a business perspective, which means that QoE is able to model all types of H2M scenarios, even if such a scenario consists of complex autonomous systems and service chains. All the QoE metrics are still valid, as an end-user may still remotely control a machine or decide to take manual control over the system. However, there are several instances including the example of the Boeing 737 MAX that we had used earlier, where full autonomy is desirable (like the plane on auto-pilot mode) where the user can supervise or be able to change the control/decision made by the AI systems. In such cases, the QoE will be affected directly by the system hardware, and the AI-powered predictive models. $QoSys$ will be able to overcome this gap that effectively measures the M2M interactions, i.e., the full autonomy of machine communications.

We therefore propose QoE_{IoT} to be a function of the traditional QoE, and $QoSys$, i.e., $QoE_{IoT} = f(QoE, QoSys)$, and define it as "*a metric that enables quality evaluation in an IoT scenario from the perspective of both humans and machines*". While the human aspect can be measured through subjective and objective human factors, the machine aspect can be measured from the machine behavior and the effect of machine performance on various business processes/entities. The entire concept of QoE_{IoT} is illustrated in **Fig. 3**.

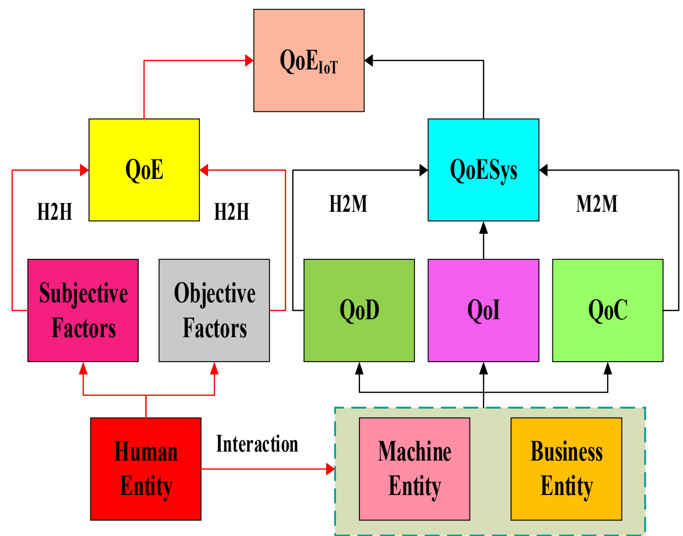

Fig. 3 The Concept of QoE_{IoT}

A. *The Human Aspect*

The human entity that involves the end-users and various stakeholders have to interact with the business entity based on some service-level agreement (SLA). These agreements are generally based on the various QoS parameters that include both the network quality and application layer parameters. Various types of QoE management models are there based either upon subjective or objective techniques for evaluating the end-users' experience. This QoS to QoE mapping may be linear/non-linear that depends on the application context [9]. More recently with the advent of the consumer IoT paradigm where H2M interactions cannot be avoided, the machine entity plays an important role. In this respect, AI technology is used by machines to learn the human behaviors and usage patterns for evaluating metrics that will help understand the user experience. For example, when the pilot disengages the auto-pilot mode and overrides all the controls, it can help the AI self-

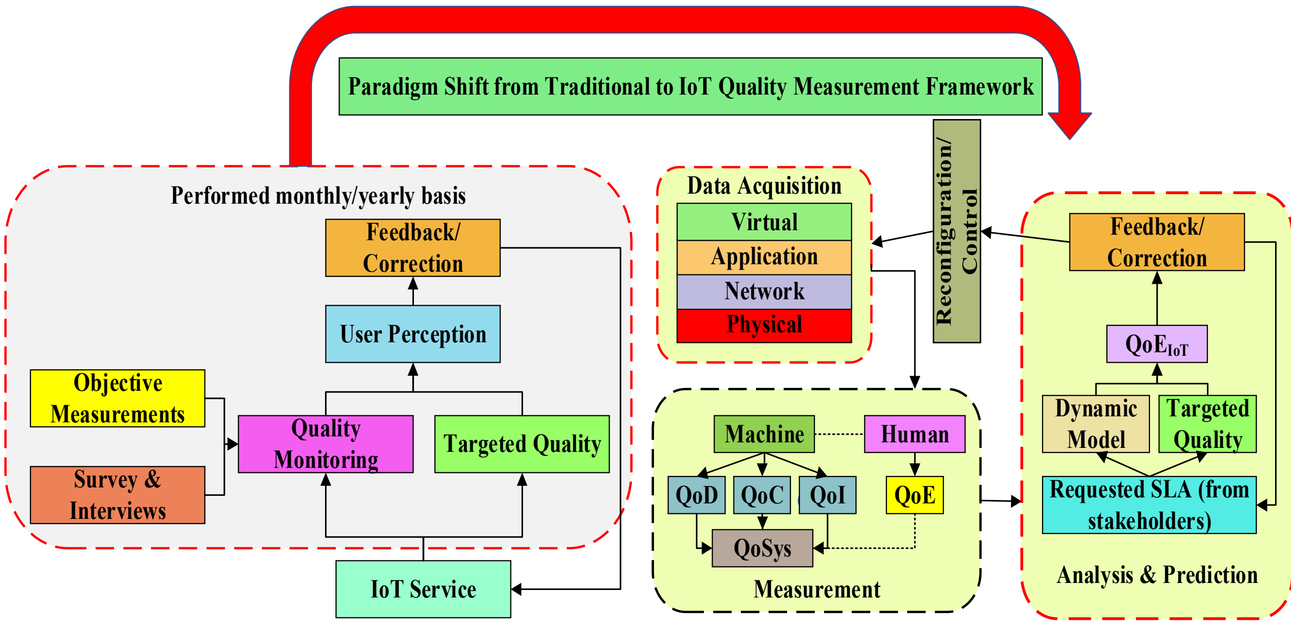

Fig. 4 The QoE Aware Framework for Consumer IoT Services

learning algorithms to decide under what conditions AI does not work well.

B. The Machine Aspect

In the IoT scenario, both humans and machines are integral parts of the complex SoS. Measuring QoE_{IoT} may help leverage the human entity to better understand the impact of machines on business processes, partially automating the machines or even understand the time when the machine hardware/software needs to be updated. Likewise, QoE_{IoT} is beneficial for the machine entity also as it helps to understand the impact of the various data sources and the information they generate on the overall service performance. While data quality can be quantified by the QoD dimension together with its metrics like accuracy, truthfulness, completeness, etc., the power of the AI algorithms is harnessed by extracting useful information from the sensed data that can be used to trigger specific events or take certain business decisions. Some of the important QoI metrics are outlined in **Table II**. With an increase of M2M transactions, another dimension that affects the SoS quality can be QoC. The idea is whenever the machines use some resources in terms of computation, storage, or energy, such consumptions should be optimized. From the discussion it is clear that QoE_{IoT} depends on the intelligence of the SoS system (machine intelligence), the end-users, their interaction with the services, and the network usage. However, the relative weightage of the different dimensions that go into predicting QoE_{IoT} cannot be pre-defined, and it depends on the specific requirements of a particular IoT service. Next, the measurement framework is presented.

IV. The QoE Management Framework For Consumer IoT Services

After presenting the uniqueness of the consumer IoT context in terms of QoE provisioning and the measurement strategy, in this section, we present a QoE-aware framework that is applicable to any generic consumer IoT service. The framework is outlined in **Fig. 4**, showing the paradigm shift from traditional QoE measurement to the IoT context. In the case of the traditional systems, data related to the relevant quality descriptors are normally obtained through surveys and interviews, together with objective measurements that are carried out by the service providers, e.g., QoS parameters for telecommunication systems. The objective and subjective measurements are then compared for investigating whether the users are satisfied with a particular service. Such an evaluation scheme makes the quality monitoring not real-time and automatic, which typically is performed on a monthly or yearly basis. Likewise, the subjective and objective measurements are done at different points in time, which makes it difficult to correlate both the scores. Consequently, although QoS-QoE models can be built theoretically, however, such models have little practical significance. Moreover, such a model will not work in real-time to adjust the quality. For e.g., in the case of a transportation system, if there is an excessive wait-time for buses to a particular destination, it cannot be known instantly to provide more buses to this particular destination. Thus, for an IoT scenario, the QoE measurement framework must change.

The functioning of a complex SoS depends on the inter-working between the IoT hardware, the centralized software and predicting models, and virtual components like data transmission and cloud resources. In this respect, we propose four distinct layers (physical, network, application, and virtual) that have a predefined scope to process various input data. The physical layer is responsible for locating the physical resources (e.g., the vehicles), and monitoring their interaction with the environment. The communication and networking aspects of data transmissions and connectivity are handled by the network layer. Issues related to packet loss, delay management, bandwidth bottlenecks are taken care of by this layer. The application layer is related to the end-user's interaction with the various services by interacting with the hardware/software i.e., the H2M interactions. Various subjective and objective human factors are considered by this layer with the intent of intelligent behavioral monitoring. Finally, the M2M interactions fall under the scope of the virtual layer. It includes entities that involve data storage, processing, timely system updates, among others.

From the acquisition block, data is passed on to the measurement, and analysis & prediction blocks respectively. Various statistical models, machine-learning, or knowledge-driven approaches are applied here for extracting the contextual nature of data to evaluate the quality both from a human and machine perspective. In accordance with the pre-defined SLA from stakeholders, the various dimensions introduced in **Table II** are utilized. Thus, the overall QoE_{IoT} combines various factors like efficiency, productivity, mean opinion scores, safety, and usability among others based on the IoT context. Depending on the nature of the service, the stakeholders can assign different weights to the different dimensions for getting a desired level of outcome.

V. CONCLUSION

In this article, we highlight how the definition of QoE is lacking in the consumer IoT context. The current QoE models are user-centric based on subjective tests that do not take into consideration the machine aspects. In this aspect, we portray this difference, how QoE is different in the consumer IoT context, what can be the measurement strategy, and finally the measurement framework for the present scenario. Explicitly, we highlight the importance of both H2M and M2M interactions, and what can be the different quality dimensions that shape the overall IoT experience. However, it should be noted that the proposed framework is purely conceptual, and it needs to be validated in various consumer IoT scenarios as a part of future work.

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