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Connected and Autonomous Electric Vehicles: Quality of Experience survey and taxonomy

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A B S T R A C T

More than ever, the automotive industry is shifting towards electric vehicles since environmental and sustainability concerns are becoming important to potential customers. Nowadays, automakers are also integrating connectedness and autonomous components in their produced vehicles to reduce time of travel and increase the safety of the drivers, passengers, vehicles and the whole transportation system. The popularity of Connected and Autonomous Electric Vehicles (CAEVs) led to a growing interest in their development with a careful focus on performance and quality aspects. In modern terms, Quality of Experience (QoE) covers important system, context, and human influencing factors that can drive improvements in the field. A rigorous survey of the literature revealed that QoE influencing factors and performance indicators are neither thoroughly identified, classified, nor modeled in an embracing framework that can be embedded in applications. In addition, QoE investigations are usually focused on specific CAEV subsystems and a broad addressing is practically non-existing. In this paper, the literature is explored for important performance aspects of CAEVs. Recent advances are critically appraised, challenges and gaps are identified, and improvements are carefully proposed. To this end, a thorough taxonomy is developed for QoE in CAEVs with a rich set of quality indicators and a framework that facilitates the integration of QoE concepts in system development. The presented contributions are expected to guide, enable, support, and accelerate future developments in the field.

1. Introduction

Some of the main social and economic problems faced by metropolitan cities are traffic congestion and accidents involving vehicles. Crashes involving vehicles have been reported to have resulted in 1.25 million deaths worldwide in 2013 alone [178]. Autonomous and Connected Vehicles (CAVs) technology has evolved greatly over the past decade [263]. This led to allowing vehicles to communicate and therefore minimizing accidents by providing drivers with timely information.

Most of existing Connected Vehicles (CVs) use Vehicular Ad Hoc Networks (VANETs) model. VANETs enable vehicles to receive real time information through a direct connection to the Internet. To that end, the use of VANETs can increase safety and awareness of drivers and vehicles [3]. Besides, LTE-Vehicle to Everything (LTE-V2X) solutions started to be deployed as commercial solutions [88] in open roads in 2018. According to the 5G Automotive Association (5GAA), first results showcase improved performance and low latency [112]. While on the road, vehicles can either connect to other vehicles (V2V) or to infrastructure (V2I). Increasing the efficiency of such communication will surely lead to transportation networks that are safe, efficient and sustainable. However, due to vehicles' high speed, dense user availability and high bandwidth requirements to support vehicle localization, and communication of real-time traffic information, several challenges exist in connected vehicles environments. For instance, using a single Information and Communication Technology (ICT) will result in performance that is sub-optimal. Multiple state-of-the-art technologies should be incorporated with LTE systems in order to develop cost-effective V2X services. Utilizing V2X services to their utmost potential necessitates optimizing perception, planning and communication in CVs. 5G technology is expected to effectively fuse the required multiple technologies in order to enable the realization of superior and efficient CV systems [66].

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To achieve a certain level of autonomy, different technologies are combined together to make Autonomous Vehicles (AVs). Such a combination is expected to eliminate car accidents, eliminate congestion, increase driver and vehicle awareness, increase the efficiency of vehicles, reduce emissions and raise the level of safety and comfort for car passengers. It is evident that AVs are rapidly advancing up their scale of autonomy levels.

Vehicles have gone way beyond the *Driver Assistance*, aka level one, which includes adaptive cruise control and lane keeping assistance. Adding self-control features, like steering and acceleration/deceleration control leads to *Partial Automation*, aka level two. Both levels, one and two, require a human driver to monitor the environment and step in when necessary. The following three levels are namely, *Partial*, *Conditional*, and *High Automation*. As the automation level goes up, human intervention is minimized leading ultimately to the vehicle driving on its own [154].

Currently, the adoption of Electric Vehicles (EVs) is rapidly increasing worldwide. EVs benefit from modern motor and rechargeable battery technologies to replace conventional Internal Combustion Engines (ICEs). In addition, EVs enjoy many benefits compared to ICE cars including their ability to operate at lower costs and higher efficiencies, being intrinsically green with minimal impact on the environment, and their electric nature that enables straightforward embedding with CAV features [147]. Combining CAVs and EVs is currently shaping the future of transportation. CAEVs blend seamlessly with state-of-the-art systems such as smart cities, smart grids, and Intelligent Transportation Systems (ITS). Undoubtedly, CAEVs and the services they provide or can be integrated within, raise the bar regarding requirements of quality. The demand is not only on the Quality of Service (QoS) provided or achieved, but more accurately on the QoE attained and as perceived by the user. Here, a user can be anybody contemplating, buying, leasing, renting or using a CAEV.

QoE is defined as "the overall acceptability of an application or service, as perceived subjectively by the end user" [113]. QoE provides an inspiring and promising concept in terms of better provision of services and products. Many factors can influence QoE. Such influencing factors are challenging due to the fact that they are interrelated, can be highly subjective and are context-specific. Traditionally, QoE Influencing Factors (QIFs) are Human (Hum), System (Sys), and Context (Cxt) factors [9]. In addition, Cost can be also classified as an important QoE influencing factor [184].

The modern literature of CAEVs is witnessing a growing attempt to integrate QoE concepts in CAEV investigations including developing models and performing optimizations [214,191,110,141,262,190,119,7,89,265,21,25,111,215,177,74,1]. CAEV designers strive to meet the quality requirements of a wide spectrum of heterogeneous Key Performance Indicators (KPIs). In addition, there is an interest in integrating aspects that help in assuring QoE in CAEVs. Investigations targeting QoE are usually narrowly focused on specific subsystems, such as video streaming over vehicular networks [1], optimization of cyber vehicular networks [89], vehicle service availability in smart cities [7], etc. Furthermore, limited or no work is reported to propose a framework for assuring QoE in CAEVs on the "system of systems level." Moreover, investigations focus on modeling QoE using a limited number of application-specific indicators within particular contexts. No study is known to present a wide and deep exploration of QoE indicators across the different CAEV subsystems and their architectural abstraction layers. Developing a QoE framework for CAEVs is challenged by the large variety of services and subsystems that belong to diverse areas as well as the fact that QoE is a relatively new concept. It is believed that such challenges are due to the lack of multidisciplinary expertise required by CAEVs. Researchers usually focus on their subsystem in a way that might prevent the reasoning about the wider perspective including the possibility of missing important subsystem hidden factors. Any CAEV system requires heterogeneous integration which present additional intersystem performance patterns and hidden factors that might go unnoticed.

Currently, CAEV features are yet to reach their full potential and be fully deployed, this is why in this paper an exploratory investigation is presented to guide, enable, support, and accelerate future developments. The research objectives include the following:

- Survey the literature to extract important features of CAEVs with a focus on performance and quality aspects.
- Create a taxonomy for QoE in CAEVs.
- Develop a framework that captures the relationships between QoE, its influencing factors, and CAEVs.
- Provide recommendations pertaining to the different criteria and indicators of the taxonomy.
- Discuss various hardware and software implementation options related to important CAEV applications such as ITS and smart cities.
- Identify open research problems.
- Identify area transformations and future trends.
- Review the main efforts towards quality CAEVs development by top car manufacturers.
- Provide the first comprehensive bibliography on the topic.

In this paper, the survey is conducted by adopting an indexing database search protocol that targets mainly *IEEE Xplore Digital Library*, *ScienceDirect*, *Springer Link*, and *ACM Digital Library*. The keywords used in the search comprise combinations of *connected vehicles*, *autonomous driving*, *autonomous vehicles*, *electric vehicles*, *taxonomy*, *QoS*, *QoE*, *performance*, *modeling*, *optimization*, *simulation*, *hardware*, and *software*. Furthermore, survey papers within the specified objectives are carefully studied in terms of methodology, coverage, and contribution. Reviewed papers were mainly published during the last five years. To capture trends and recent accomplishments, information from websites of important industrial firms and authentic technology news sites was used in some parts of the paper.

The methodology of this paper development comprises the following:

- Develop the search protocol
- Survey the literature
- Develop classifications of related work
- Develop the taxonomy
- Develop the QoE framework
- Present recent advances both in the industry and academia
- Present recommendations on various important aspects
- Identify and propose directions to improve existing work
- Identify and propose future work
- Conclude with open research questions

A variety of survey papers that explore different aspects of CAEVs were identified in the literature. None presented a focus on QoE or explicitly addressed any of its influencing factors. However, the surveyed papers were a rich source of QoE performance indicators. In [228], an evaluation framework for CAV applications was presented with an interesting explicit set of performance indicators. Other survey papers provided overviews, presented the state of the art, and identified future challenges within CAVs [71,159,154,17]. In [159], the focus was on use cases, such as platooning and autonomous lane change, while in [154] technological aspects were surveyed. In [17], comfort in moving-base simulators of autonomous driving was explored. Other papers within CAVs comprised surveying architectures and enabling technologies [211], Artificial Intelligence (AI) for vehicles [139,230], and sensor technologies [155]. Several different topics related to EVs were discussed in the literature. EVs, energy harvesting, and performance were reviewed in [205], managing EVs smart grid using AI was the topic in [12], managing smart grid with EVs using AI [198], Microgrid control was the topic in [28], while energy optimization in EVs charging was the topic in [8,115]. Integration of solar energy was the topic in [255].

The paper is structured so that Section 2 presents background information on QoE in a tutorial style. In Section 3, a comprehensive survey is presented with a focus on performance aspects of CAEVs. In Section 4, QoE within CAEVs is surveyed. In addition, the taxonomy and framework developments are presented. In Section 5, discussions and recommendations are provided. Furthermore, CAEV industries are explored and the main trends in the area are presented as well as their outlook. In Section 6, the paper is concluded by highlighting important open research questions and presenting future work.

2. Quality of Experience

Historically, the performance of a system was evaluated in terms of the Quality of Service (QoS) provided to users. QoS principles were not intended to capture the user's subjective perception of quality or degree of satisfaction. The concept of QoS as experienced by the user was initially conceived by the International Telecommunication Union-Telecommunication Standardization Sector (ITU-T) in 2008 as being "influenced by the delivered QoS and the psychological factors influencing the perception of the user" [113]. At a later stage, the term QoE was introduced along with the tremendous advancements in ICT. QoE is defined as the overall acceptability of an application or service, as perceived subjectively by the end user [113]. Thus, the user-centric concept of QoE extends the notion of network-centric QoS [24]. The main focus of QoE is to evaluate quality perception and gather input to guide optimization of different technical parameters.

QoE can be influenced by a wide range of factors, which are strongly interrelated and present a high level of subjectivity. A QoE Influencing Factor (QIF) is commonly categorized into Human Influencing Factors (HIFs), System Influencing Factors (SIFs), and Context Influencing Factors (CIFs). An HIF represents any property or characteristic that is human related. Such a factor can describe the demographic and socio-economic background, the physical and mental constitution, or the user's emotional state [24]. An SIF, also known as the QoS factor, refers to any property or characteristic that determines the quality of an application offered by the system. An SIF can be classified into content-related, media-related, network-related and device-related [24]. A CIF denotes any property that describes user's contextual situation. CIFs refer to physical, temporal, social, economic, task, and technical characteristics [121]. In this paper, we adopt a classification of QIFs that comprise Human, QoS, Context, as well as Cost.

Until recently, significant effort was put to develop standards that are applicable to application areas as well as sets of QoE metrics that can capture important performance aspects of applications. The available standards on QoE describe the technical requirements for audio and video applications [100,101,98,104,102], digital media content [106], visual comfort [103] and perceptual quality of 3D contents [105]. In [158], an intensive set of examples of services where QoE methods can be used was presented, namely speech communication systems, text-to-speech synthesis, audiovisual communication, multimedia conferencing and tele-meetings, audio transmission, spatial audio rendering, haptic communication, video streaming, web browsing, gaming, task-based applications, and wireless networks.

True measures of QoE must ultimately take into consideration the end-user subjectivity and the impact of additional contextual and user-related factors. Consequently, subjective and objective quality assessment methods have evolved over the years, aiming at modeling the impact of both technical (QoS-related) and non-technical (e.g., user, context) influence factors on QoE [9,214,191,110]. From the practical point of view, the challenge remains how to use QoE models to optimize the end-user experience.

3. Performance aspects of CAEVs

A CAEV is the blending of the three types of vehicles, namely CVs, AVs, and EVs. Each type of vehicle has been studied extensively in the literature as related to architectures, designs, hardware and software implementations, solutions to problems, applications, and an interesting variety of analytical patterns that aid performance evaluations (see Fig. 1). CVs can be characterized in terms of their vehicular communication and networking options. AVs can be clustered around the adopted applications, localization, navigation, or their computational models. Moreover, EVs can be distinguished by the characteristics of their applications and their energy aspects. In the following subsections, an extensive survey of the literature is presented with a focus on main contributions, solution strategies, appealing characteristics, and performance aspects that can influence QoE.

3.1. Connected vehicles

The rapid growth of heterogeneous vehicular networks transformed connected vehicles into intelligent computational devices on wheels. Vehicle to Everything (V2X) communications combine Vehicle to Infrastructure (V2I), Vehicle to Devices (V2D), Vehicle to Pedestrians (V2P), and Vehicle to Cloud (V2C) technologies. Vehicular communications and networks technologies are classified into three categories: intra-vehicle communications, inter-vehicle communications, and inter-vehicle networks. The intra-vehicle communications category includes wired and wireless technologies used to provide connectivity with in-vehicle smart devices or other installed On-Board Units (OBUs). The inter-vehicle communications category covers namely the IEEE 802.11 family and base station driven technologies. The inter-vehicle networks category contains the existing network architectures deployed for connecting the vehicle with the outside environment including, among others, transport infrastructure, pedestrians, and data centers.

3.1.1. Intra-vehicle communications

Connected vehicles are equipped with a variety of interconnected devices. On board devices are wired to electrical control unit devices, which communicate with each other via a core network. There are several types of core network buses that can be used inside vehicles, such as controller area networks (CANs), local interconnect networks (LINs), media-oriented systems transport (MOST), FlexRay and Ethernet. Many challenges are faced by core networks in CVs mainly security issues and network performance related to both size and complexity. In [143], the diversified attacks to which a connected vehicle can be subjected were analyzed. Solutions to avert attacks through the CAN bus, ECUs, and in-vehicle infotainment systems were presented. The solutions included the use of authentication protocols for the CAN bus, or the use of in-vehicle network behavior anomaly detection which extends the detection mechanism of intrusion detection systems (IDSs) for computer networks. Sun et al. [219] proposed replacing the wired technologies (CAN, LIN, MOST, FlexRay) with short-range wireless communication to provide communication between the different units within a vehicle or between them and any wearable sensor placed on the driver or the passengers.

Various sensor-networks based wireless technologies were explored for communication within the vehicle or with the outside environment. In [219], integrating smart wearables and intelligent

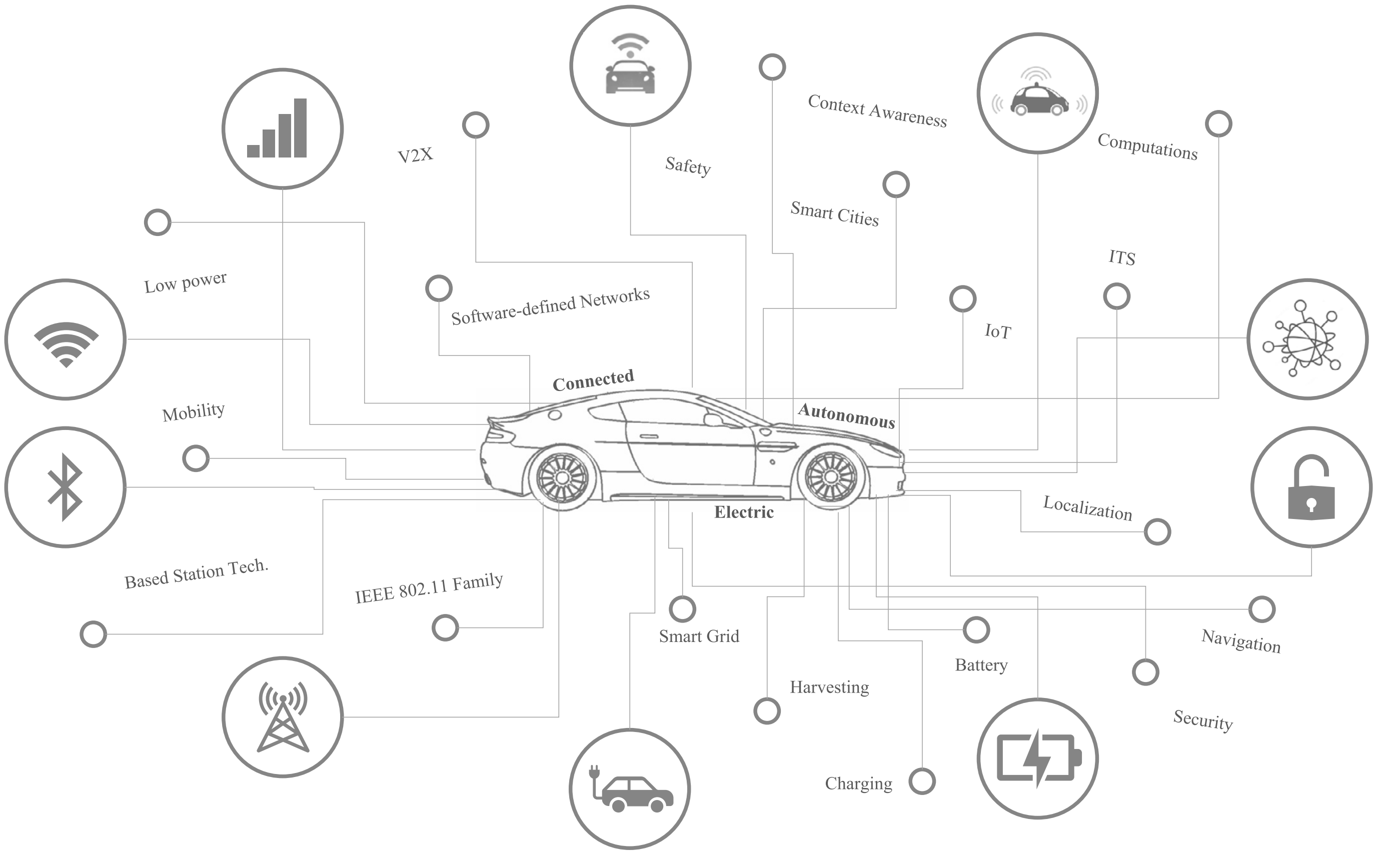

Fig. 1. The main CAEVs subtopics addressed in Section 3.

vehicles (WeVe) in vehicular networks was explored. A hub-centric communication architecture for WeVe was proposed that can be easily integrated with the existing network architecture. Several short range WeVe communication technologies can be used for the internal network, such as Bluetooth, Zigbee, and Ultrawideband (UWB). UWB was singled out as a promising technology because of its high throughput (1 Gbps) and low power consumption (less than 1 mW). In [145], the benefits of implementing a blind zone alert system based on intra-vehicular wireless sensor networks are investigated in order to improve driver's safety. Vehicular safety of in-vehicle sensor networks was also investigated in [126], where an AI-based technique for monitoring, reporting and autonomously recovering of vehicles was designed and implemented.

3.1.2. Inter-vehicle communications

IEEE based technologies and base station driven technologies are commonly used in V2V and V2I communications [251,99]. In addition, massive data are collected from monitoring OBUs and in-vehicle sensors and devices to assure good user's experience and quality of service. In [264], the relationship between Internet of Vehicles (IoV) and big data in vehicular environment was investigated. The study showed that IoV can support transmitting, storing, and computing of big data, while big data can improve IoV in terms of network analysis, design, and performance assessment. Improving the QoS in terms of network resource utilization is investigated in [20], where a location-based and information-centric architecture was proposed to improve the content request process and reduce the problem of broadcast network utilization. In the same token, in [210] it was suggested to offload delay-tolerant data traffic from the data networks to the connected vehicle networks by using a distributed data hopping mechanism to allow delay-tolerant traffic routing. The authors in [274] proposed a multiple-vehicle algorithm enabling collaborative download of data. In [180], a method is proposed to optimize system reliability and efficiency in high mobility vehicular communications. This method consists of adaptively choosing cooperative or non-cooperative transmission schemes to achieve the best QoS vehicular network performance in terms of outage probability, throughput, energy efficiency, packet delivery ratio, packet loss ratio and average end-to-end delay.

Recently, vehicular connectivity techniques underwent an evolution to support V2X communication enabling vehicles to communicate with OBUs, other vehicles, pedestrians, infrastructure, cloud, and network. This created many challenges for network providers in modeling QoS frameworks and assuring a good QoS. The main causes of such challenges are due to low incident detection rates, massive data transmission, and vehicular mobility. An analytical framework was developed in [173] to quantify the system capacity and delay performance, while a modeling approach is proposed in [150] to support design, deployment and monitoring of a QoS system in a systematic manner. In addition, many techniques are proposed in the literature to improve QoS in V2X communication technologies. In [186], techniques for automatically detecting traffic incidents in a traffic scenario are proposed to allow drivers to avoid congestion which resulted in increasing incident detection rates and shortening peak queue values.

3.1.3. Inter-vehicle networks

Embedding VANET's communication technologies into Internet-of-Things (IoT) networks and base station driven technologies, such as 4G or 5G, provide V2I and V2N services with high data rate, comprehensive QoS support, ubiquitous coverage, and high penetration rate [251,218,66,172,52]. However, the performance of the resulting networks faces many challenges due to the increasing number of fully autonomous vehicles.

First, high mobility of vehicles and complex traffic scenarios lead to severe degradation of vehicle networks connectivity. In [206], this challenge was addressed for 4G LTE systems by leveraging the spectrally efficient air interface, deploying a cost-effective network, and providing the ability to support different types of communication systems. This enabled an LTE system to support cost-effective V2X services. In [209], the integration of Drone Assisted Vehicular Networks with V2V and V2I communications was suggested to overcome the high mobility challenge. Moreover, in [55], the challenge of providing stable and high-quality on-board Internet services for high speed vehicles in heterogeneous wireless networks was addressed. A concurrent multi-path transmission scheme based on real measurements in a typical high-speed environment using existing 3G and 4G technologies was proposed, together with an adaptive network scheduling algorithm to enhance on-board Internet services. Currently, new vehicles by Cadillac and Audi integrate Internet connectivity using the Dedicated Short-Range Communication (DSRC) technology to enable V2V and V2I services. Cellular V2X (C-V2X) has emerged as a high-performance technology. C-V2X promises improved QoS, coverage, reliability, capacity, and congestion control in dense networks—as compared to DSRC.

Second, the increasing number of vehicles in vehicular heterogeneous networks may not only overwhelm LTE network utilization, but also incur high cost. In [3], the efficiency of LTE use was optimized by proposing a clustering mechanism that includes a self-location calculation algorithm. This algorithm enforces a policy of fair use among the cluster members and reduces the link failures rate among vehicles as well as between each vehicle and the 3G/LTE network.

Third, in the existing collision avoidance algorithm used for V2V broadcast, multiple resources per schedule assignment are reserved. This leads to the loss of many data packets if an assignment collision happens. In [77], a mechanism that reduces data collisions in LTE V2V broadcast applications was proposed.

Fourth, supporting the various services of connected and autonomous vehicles with a wide range of on-board sensors requires high-speed and low-latency services. Millimeter wave (mmWave) communication systems have been proposed to overcome the speed and latency limitations of existing technologies [31,10]. In [221], a framework for modeling mmWave highway networks was proposed. It was proven that a reduction in the outage probability of the Signal-to-Interference-plus-Noise Ratio (SINR) can be obtained by the deployment of low-density base stations.

Improving QoS in VANET networks is the subject of several research studies. In [140], a programmable control principle based on the software-defined networking model was introduced. This control principle was used to optimize the scheduling of delay-tolerant data traffic within vehicular, IoT or other data networks without deploying additional infrastructure. In [207], an architecture was developed for context-aware heterogeneous vehicular networks allowing for the dynamic selection and configuration of communication profiles based on context conditions and application requirements. In [114], congestion control in VANET was improved by designing a cross-layer protocol framework for traffic management which allocated dynamic time slots to traffic lights and monitored the channel busy status.

The deployment of different technologies in VANET networks is challenged by two main factors. The first factor is the efficiency and reliability of service discovery and selection for vehicles in smart cities. The second factor is the utilization efficiency of the heterogeneous resources. In [92], a proactive network association mechanism was proposed by taking coordinated multipoint transmission into consideration under the Heterogeneous Cloud Radio Access Network (H-CRAN) architecture in order to reduce latency and guarantee ultra-reliable communication. Traditional vehicular networks do not take into account human characteristics. With the growth of vehicular applications, powerful communication and computational support is required without additional infrastructure deployment. In [85], utilizing vehicular fog computing (VFC) is proposed in which communication and computation is carried out by vehicles. Cultivating the resources of individual vehicles will lead to a considerable improvement in the quality of services and applications.

3.1.4. Inter-vehicle network architectures

As the automotive industry witnesses an increasing focus on connected cars, more IoV solutions are becoming prominent through advancements of networking, 5G, and IoT [123]. However, research in this area mainly focuses on the optimization of mobility models and communication performance to achieve efficient traffic management. Little or no focus is available on the interconnection of heterogeneous smart vehicles. In [73], an Artificial system with Computational experiments and Parallel execution (ACP)-based vehicular network framework was designed to achieve a more reliable, efficient, and ultra-high data rate communication among vehicles and infrastructures. In [249], this challenge was faced by proposing a local traffic information collection structure with the help of IoV and an optimized data transmission model. Handover may not be an efficient scheme in H-CRAN. A cluster-based framework was developed in [197] to assure continuous availability of diverse cloud services. A location prediction method was also adopted to determine the future location of the vehicle and provide the requested services ahead of time.

Emerging automotive ITS applications can further improve AVs performance by providing continuous Internet services and cooperative functionalities, namely, cooperative adaptive cruise control [239] and platooning [239,160]. In [160], it was shown that potential benefits can be achieved by using unassembled data collected over V2X connections. Five use-cases were considered and analyzed: vehicle platooning, lane changing, intersection management, energy management and road friction estimation. In [72], different approaches aiming at improving energy efficiency were investigated with focus on a control and planning architecture for CAVs. VANET Network failure was investigated in [50] to implement a cooperative communication technique through developing a distributed algorithm that reduces the delay during the re-transmission procedure. Current vehicular network architectures are faced with the limitation of existing wireless links in supporting massive and real-time data transmissions. The topology of vehicular networks has a significant effect on network performance, reliability and adaptability. Exploring topologies of urban wireless sensor networks for road traffic management is investigated in [61]. The conclusion was that protocols and algorithms can be better evaluated by replacing generic random graphs with graphical models for urban wireless sensor networks.

3.1.5. Security in vehicular networks

Dissemination and sharing of information among vehicles are among the primary advantages of vehicular networks. However, these networks are susceptible to various attacks since they are highly dynamic, distributed and of open nature. Several research studies are conducted to face these challenges. In [250], a specific mechanism of learning enhancement was designed in order to ensure that all vehicles share genuine information. In [6], an automated secure continuous cloud service was introduced to solve security issues. In [152], the need for trust models was highlighted especially related to the characteristics of data-oriented trust models, entity-oriented trust models and hybrid trust models. Message dissemination efficiency in terms of traffic efficiency and road safety of vehicular networks was investigated in [269]. A holistic comparison of the different solutions offered by the VANET research community was provided in terms of handover, data dissemination, gateway selection, QoS and other factors. In [273], some promising applications were proposed to reduce network traffic and provide real-time services using massive peripheral nodes. A location-based service usage framework was also proposed to provide an adaptive privacy protection solution.

3.2. Autonomous vehicles

When asked about autonomous vehicles, certain people are excited to use one; others are skeptical [117]. Before AVs can be used satisfactorily hardware and software should be efficiently designed to recognize the location of the AV, to navigate the AV and dynamically define its path, to safely cross an intersection, to secure vehicles against all kinds of attacks, to make sure the AV can find a parking spot and can park itself, etc. Traffic conditions monitoring is expensive, time consuming and can be subject to increasing errors. Security and safety of the autonomous vehicle and the person using it is a challenge that should be overcome to gain the trust and satisfaction of users.

The localization of a vehicle is the identification of its location on a global coordinate system [129]. The localization system of an AV usually goes hand in hand with the perception system that identifies the driving environment of the vehicle defined by other users on the road, obstacles, traffic light systems; as well as the planning system that uses inputs from the localization system and the perception system to build the path of the AV and define its driving actions.

Localization of an AV [130] can be sensor-based or cooperative. Sensor-based localization techniques use on-board sensors to determine the vehicle global position in some coordinate system. The main sensors used for these techniques are GPS, inertial motion units (IMUs), radio detection and ranging (RADAR), cameras, light detection and ranging (LiDAR) and ultrasonic sensors. GPS sensing relies on at least four satellites to position a vehicle at low cost. However, the accuracy of this technique is low (few meters) and it cannot be used in long GPS outage conditions. To improve GPS sensing, it is often combined with IMUs in the dead reckoning method using accelerometers to measure linear accelerations and gyroscopes to measure angular velocities of the vehicle in order to find the position relative to its initial position. Using GPS and IMUs as standalone methods results in high localization errors; better results can be achieved by combining data from other sensors. Combining Global Navigation Satellite System and an Inertial Navigation System [263] resulted in localization with centimeter accuracy.

Camera-based localization techniques can achieve better accuracy than standalone GPS and IMUs. Several camera-based methods exist [130]. In [120], three cameras were used in the detection of the Road Surface Marker (RSM) features; then RSM features are captured using a probabilistic noise model and embedded the algorithm used for localization. Even though better accuracy can be achieved with camera-based sensor methods, they are affected by weather and illumination conditions. To improve these methods, data from GPS, IMUs and camera sensors can be combined in order to achieve improved positional errors [130]. RADAR-based techniques use a RADAR sensor that emits periodic radio waves that reflect off obstacles to the receiver; therefore, allowing to measure the distance between vehicle and target. Even though these methods have low power consumption, but their accuracy is few meters. LiDAR-based localization methods are more accurate and robust than RADAR-based methods. A LiDAR sensor measures distances to a target by using multiple laser beams that reflect off obstacles back to a receiver. The accuracy of this method is high (few centimeters); however, its disadvantages are high power consumption, high cost and high dependence on weather conditions. Some localization methods used low-cost ultrasonic sensors which use a mechanical wave of oscillating pressure that reflects off obstacles and propagates back to a receiver. This method is time consuming and inappropriate for AV localization.

Some localization techniques are cooperative techniques that integrate both on-board and off-board data [129]. Localization can also be done using the concept of IoVs where each AV can connect to the inter- and intra-vehicle networks and vehicular mobile internet and thus access a wide range of information that improves the accuracy and robustness of localization, improving the line of sight of on-board sensors at low cost. These techniques use cellular, Wi-Fi, and UWB radio communications to calculate the distance to the broadcaster based on four principles: arrival time, arrival time difference, arrival angle, and the strength of the radio signal. For instance, the authors in [39] used vehicle communication and smartphone sensors to improve localization in vehicular ad-hoc networks.

Various applications to autonomous vehicles have been discussed in the literature. These applications are not necessarily mutually exclusive [64]; they vary in usability, in the service provided and in their design. The Autonomous Parking Pilot for example is a practical solution to the parking problem where the AV, after dropping off its passengers, can direct itself to a parking space and then when needed it can head to a given address to pick up back passengers.

Autonomous vehicles have great potentials in the areas of shared AVs (SAV) to complement public transport [64,137,132]. Even though non-motorized transportation is ideal for the environment; however, shared AVs in conjunction with public transport are the next best thing to reduce individual car transportation. These SAVs can be designed to operate exclusively driverless with no driving wheel or pedals.

On the other hand, for individuals who would like to rely occasionally on autonomous driving, private AVs [64] can be designed so that the autonomous driving feature can be turned on automatically to avoid accidents or on demand by the driver if he/she wishes to do something else while the AV drives itself.

Autonomous vehicles can play a major role as service providers. For instance, Autonomous Delivery Vehicles [64,30] are small self-driven vehicles that can deliver parcels or goods to people right to their doorsteps or carry pallets in ports, factories or construction sites. AVs can provide services other than moving people or goods. Unmanned Aerial Vehicles (UAVs) can play the role of flying base stations to widen the coverage of terrestrial mobile communications [220]. This is needed to cope with the ever-increasing traffic demand due to the heavy use of smart phones.

The design and proper operation of AVs require extensive research, planning and coordination of a number of tasks resulting in the generation of a large number of computational algorithms to implement these tasks. For instance, one of these tasks is to locate the AV in a dynamically changing environment. Several algorithms [148,263,39,129,120,130] exist to help implement the localization task. Other algorithms [268] are required to navigate the AV to its destination. The path planning algorithm [30] parameterizes the motion primitives and optimizes them as a non-linear programming algorithm; whereas the authors in [259] use neural inverse reinforcement learning to navigate the AV. In [237], navigation as an optimal control was defined as a problem that generates the path of the AV while optimizing a relevant parameter such as the distance traveled. Even the parking problem got its share of algorithms [133] that can lead the AV which is seeking a parking spot to the appropriate parking facilities in a distributed way to save time.

When AVs are used as public transportation, scheduling and routing algorithms as well as admission control algorithms [132,137,128] are needed for appropriate decision making to plan the traffic flow and avoid congestion in the most economical way. A linear program is adopted to solve the scheduling problem [132] and the admission control problem is based on a genetic algorithm. The authors in [128] use the family model for scheduling AV fleets, whereas the authors in [56] used game theory techniques for decision making to avoid congestion of AVs.

Just like proper hardware and software replaced drivers of AVs, intersection controller units and the right communication algorithms can be used to manage and control traffic intersections eventually replacing traffic lights [40,146] while reducing delays, number of stops and fuel consumption without jeopardizing safety. In order to safeguard the security and safety of these AVs and the privacy of those who use them against any types of attacks, proper algorithms are needed to detect and prevent cyber-attacks on every smart technology used to operate them [23]. The security algorithms are spread over the various layers involved in the design of AVs; thus, each function and each service is designed with security algorithms embedded in them [182,213,248,236,117,75].

3.3. Electric Vehicles

Research in Electric Vehicles tends to cluster around studying the effect of EVs on the electric power network. Regulatory and policy issues are also active areas of research as well as integrating EVs safely into society. As far as QoE related issues, most of the research is geared towards enhancing QoS and QoE factors in order to increase the adoption of EVs. Enhancing the distance an EV can travel on a single charge is one area of research. This can be done through multiple ways such as minimizing the energy consumption of subsystems in an EV, increasing the efficiency of energy storage devices in an EV, maximizing the harvested energy when an EV is operational or reducing the distance between charging stations by optimizing their locations so that they reduce the maximum distance an EV should travel before it can recharge. Another QoE factor which is actively being researched is the actual charging time taken by the EV. Finally, the security of the EV as a connected vehicle is also an active area of research.

Most of the surveyed EV literature can be divided into five categories. The first category is papers talking about problems in adoption of EVs and possible solutions. The second category is papers talking about EVs in fleets and car sharing systems. The third category is papers discussing the effect of EVs on the existing electric grid. The fourth category is papers discussing issues related to making EVs more efficient or making their performance better. The fifth category is papers which discuss policy issues related to EVs.

In the category of investigations discussing the adoption of EVs, [125] states that it is unknown how to minimize the barriers to wide adoption of EVs. Their solution is to develop a model to estimate the potential for a Battery EV to replace one of the two conventional cars in a household to satisfy the driving demands of the household in a viable way. The problem to adoption of EVs in [118] is that little information is available about how owners of EVs are using their vehicles and what limitation of an EV and to what extent is it affecting the use of the EV on a daily basis. Their solution is to use real EV data to classify daily use and types of trips taken by owners of EVs. This is done to come up with enough information to know how a household decides to use an EV versus a conventional vehicle for a specific trip. [29] affirms one of the most important factors affecting the purchasing decision of an EV is the service component. Their solution is to identify the main sub-systems of the power supply system to identify the critical success factors to be used in marketing. The main problem identified in [19] is that EV users have anxiety over running out of electricity before finding a place to charge. To lessen this anxiety, usually EV manufacturers have large batteries to enable the EV user to take the user on one charge for long distances. This leads to less efficiency of the EV coupled with a high cost and time of charging. Their solution is to study where and when to deploy wireless charging stations with solar panels and batteries to enable vehicles to recharge while on the road. Such solution is expected to lead to users having less anxiety while enabling manufacturers to reduce the battery size which will lead to improvement in emissions as well as cost and time of charging. In particular, CAEVs share the limited battery power while also having another factor affecting user adoption which is operating in areas where no communication is available. [271] proposes to implement a delay-tolerant network topology to enable CAEVs to operate even in areas where communication is bad. A side effect of such a topology is to optimize CAEVs recharging.

Moreover, and still under the adoption of EVs; in [266], locating a charging station and how much time it takes to charge an EV are identified as the main problem for EV users. Their solution is to develop decision-making framework for charging which is optimal and sustainable. Both [135] and [192] affirm that EVs are not being adopted at a rate which is satisfactory. The solution in [135] is to survey consumers and their attitudes towards EVs to deduce what to do to make EVs more desirable to customers. In [192], it is proposed to develop a model of how users adopt EVs and use it to predict which parameters affect EV adoption and therefore push for developing policies to make adoption of EVs better. In fact, in China, despite incentives to adopt plug-in EVs, Chinese users are not shifting to EVs at a satisfactory rate according to [246]. Their solution is to conduct a study to study the impediments to wide adoption of EVs and therefore recommending policies to be adopted for increasing the rate of adoption of EVs. In [204], the inefficiency of ICE vehicles is identified as the main reason for adoption of other types of vehicles. The solution is to make EVs more attractive by making them autonomous and able to communicate especially with other vehicles.

Papers in the second category discuss issues related to fleets and car sharing systems. In [272], limited battery capacity and lengthy charging times are blamed for EVs not matching the utilization of non EVs in a car sharing system. The solution is to implement a system that would make optimized decisions regarding vehicle assignment as well as allow vehicle relays and introduce incentives for users to use vehicle relaying. One of the critical problems in EV sharing systems is the imbalance in stock across EV stations according to [4]. The solution is to develop a model to be used to predict the optimal distribution of EVs. In order to increase the adoption of EVs in vehicle charging fleets, [34] suggests developing a model to optimize the placement and number of charging stations as well as predict when to tell the user to drop the vehicle at a charging station versus leaving it at their destination. [109] suggests developing a model also but this time to compare EVs to ICEs and emphasize to car sharing companies the ecological potential of EVs. [149] suggests also developing a model for comparing EVs and ICEs in terms of profitability and highlight to potential customers how profitable EVs are compared to ICEs. [22] highlights to vehicle sharing companies the fact that increased demand for ICEs may lead to shortage of fossil fuels while increased demand for EVs will not have the same effect since EVs run on energy that can come from renewable sources like solar and wind.

The effect of EVs on the grid is the main theme of the third category of papers surveyed. In [270], both the QoE of the EV user as well as the load capacity of the existing power grid are the main issues to be taken into consideration while scheduling charging and discharging of EVs. The solution is to enable the charging scheme of an EV to be aware of the travel plans of its user as well as his/her driving patterns. In addition, a cooperative scheme for charging and discharging of EVs parked in the same parking lot is suggested as a way to improve the QoE of users of EVs and at the same time improving the load capacity of the power grid. In [60], it is suggested to develop a controller for charging EVs that will schedule EV charging to meet QoS and QoE requirements while at the same time taking into consideration the load on the grid. This is expected to make the wide adoption of EVs not significantly affecting the load on the electric grid. In [183], it is suggested to introduce multiterminal low-voltage direct current elements in the network to distribute the charging demand of EVs between multiple transformers. In fact, [127] suggests using EVs to normalize the supply and demand in the electric grid. Electricity demand in a normal electric grid fluctuates between periods of high demand and periods of high availability which do not usually occur in sync. EVs could be used to store energy in high availability periods and later provide it in high demand periods. To predict the impact of the wide adoption of Autonomous EVs (AEV) on the grid, [267] developed a model for AEV energy consumption and optimization of routes for saving energy and minimizing charging.

The fourth category of papers discussed ways of making EVs more efficient. In [275], a new heat pump is designed that minimized energy used by the largest energy consuming subsystem in an EV, namely the heating system. In [176] the efficiency of electric furnaces is improved by placing the furnace at the bottom of the EV in addition to several other modifications. In [68], a new control mechanism is developed that leads to minimizing the size and power consumption of the electric motor in an EV. In [65] a tool is developed to simulate an electric battery. This tool enabled the evaluation of the environmental impact of a battery as well as choosing the appropriate battery for a specific EV. In [253], a Lithium Ion battery model is also developed. This model is used to investigate existing battery thermal management strategies to minimize temperature variations across the battery and therefore prolonging its life-cycle and improving its safety. This is expected to lead to adoption of Lithium Ion batteries in the automotive industry. In [247], a hybrid charging scheme using both wireless and solar charging to optimize energy delivery at all times in wireless sensor network. Such a scheme can be used by EVs to optimize energy availability. Minimizing the energy in multi-sensor networks is achieved in [80] without compromising performance. This is done by developing a sensor management system that is automatically aware of network objectives while trying to minimize energy consumption. This system makes use of a model of the behavior of the multi-sensor network to enhance collaboration between sensors. The model is used to increase the adaptability of the system to the dynamics of the environment, the criticality level of the situation and the resources available to each sensor. Such management system and models can be used in EV networks to minimize energy consumption of EVs as well as to optimize charging and discharging of EVs. Optimizing the velocity profile of an EV is used to minimize the energy consumption of an EV and therefore extend its miles-per-charge in [107]. This brought the performance of EVs well into the range of ICEs and therefore made EVs more competitive compared to ICEs.

Policy issues are discussed in the fifth category. In [147], a study is conducted to inform policy makers about mini-EVs. This study is expected to enable policy makers to understand better how to classify mini-EVs and remove any regulatory uncertainty. Policies exist to reduce environmental impact of vehicles, but none is effective. This is why, in [108], a model is developed to estimate the environmental effect of a vehicle. Such a model can be used by designers to optimize their designs to minimize environmental effects. It also can be used by policy makers to make their policies more effective. Policies to increase the adoption of EVs are also not effective in many communities. Here also, in [257], a model is developed to simulate the effect of a policy on the preference of a vehicle for a consumer. In [176], it is suggested to introduce a policy that would force EV makers to include artificial noise in their vehicles to increase the safety of the EV on the road.

Several other papers are reviewed which did not fit in any of the above five categories. In [86], a model for an EV is developed to be used by designers to test their designs before implementation. This model can also be used as a Hardware-in-the-loop subsystem that can enable better prediction of how the design will end up different from the original design. In [170], the cybersecurity of EVs is studied and a response model is built that would isolate infected EV charging stations while, at the same time, making EV charging station available for EVs to use. In [16], an anti-jerk model-predictive cruise controller is developed so that users would use cruise control more often and therefore increase the efficiency of vehicles in general and EVs in particular.

4. Quality of Experience taxonomy for CAEVs

QoE in CAEVs is of diverse aspects. The diversity of quality-related aspects, and characteristics, naturally stems from the composite nature of the assessed vehicular technology or service within CVs, AVs, and EVs. To that end, modeling QoE within CAEVs mandates the incorporation of various performance aspects related to cost, context, and human–in addition to formulations based on QoS indicators. The wide range of QoE aspects in CAEVs calls for the development of a taxonomy that aids the identification, classification, selection and incorporation of the presented indicators in applications. Indeed, the proposed taxonomy is multifaceted and significant in size due to such an intrinsically diverse area.

4.1. Quality of Experience in CAEVs

A variety of QoE-specific investigations are identified in the literature where a great focus is on video and multimedia applications. In-vehicle video and multimedia applications deal with challenges, such as managing mobility of wireless channels among vehicles within IoV environments [214]. To address such a challenge, Sodhro et al. utilized an AI-enabled QoE optimization based on power- and buffering-awareness during media communication. Moreover, dissemination of video over VANETs in real time is challenged by its tight requirements of quality, dynamic network topology, and the environment of the broadcast [191]. In [191], a mechanism based on QoE-awareness is proposed for real-time video delivery over V2V VANETs, while probing parameters, such as, the importance of a video frame, position, and an estimate of the video distortion. The use of in-vehicle live video, including terrestrial broadcasting mobile television to vehicles, is seriously challenged by scarce network resources, vehicles movements, time-varying channel conditions, and attaining a satisfactory performance as observed by the user [110,262,190,265,177]. To that end, schemes are tailored to support video transmission with QoE assurance based on adaptive error correction, grouping-based video segments storage and seek, multipath delivery, speculative prefetching, and multi-criteria protocols that combines different indicators. In [265], the authors propose algorithms for resource allocation in vehicular networks to improve video streaming. The algorithms are for the joint operation of short-range (SR) V2V and long-range (LR) LTE communications. Furthermore, Eiza et al. in [74] employed situational awareness and an ant colony algorithm to optimize routes between the communicating vehicles based on QoS indicators. With focus on video uploading, [119] presents the development of a QoE-aware mobile cloud scheme. The scheme is tailored for the roadside vehicular network and can adapt according to the video bitrate to select the proper wireless interface.

Other QoE-related investigations are identified in the literature that range from improving vehicular communication, optimizing vehicle service availability in smart cities, to enhancing Vehicle to Grid (V2G) applications. In [21,25,215], different strategies were presented to improve vehicular communications efficiency and security. Bozkaya and Canberk [21] propose a software-defined power management and flow model in vehicular networks. The proposed model aims at addressing challenges, such as dynamic topological changes and vehicles transmission interference, in mobile and limited transmission range Roadside Units (RSUs). Here, vehicles are classified based on the attained QoE level and accordingly assigned an RSU with better communication performance. In [25], the performance deficiencies in conventional cloud-based solutions were addressed, such as bottlenecks of network bandwidth and high delay, by demonstrating the concept of Edge Computing Enabled IoV (EC-IoV). The investigation includes the development of a node selection strategy based on QoE. Users can decide on selecting a proper edge node to achieve a satisfactory QoE per quantities of vehicles. In addition, Sparrow et al. [215] studies the implications of securing communication channels on the operation of unmanned vehicles. To that end, the authors carefully examine the balance between the provided QoS and the attained QoE over a multi-hop communication link.

Investigations in the literature go beyond vehicular communication aspects. In [7] Smart Vehicle as a Service (SVaaS) is promoted through an investigation on providing uninterrupted services within smart cities. The solution uses a prediction mechanism for future localization of vehicles. QoE-based service selection is used to identify the needed services before the arrival of vehicles. Furthermore, Hui et al. present a contract-based pricing mechanism for V2G networks under asymmetric information that enables finding the optimal contract. To that end, the challenge is to enable aggregators choosing the contract item designed for its type that maximizes QoE.

From the identified QoE-specific investigations, several modeling styles, optimization procedures and algorithms, quantification methods, and validation patterns are identified. Modeling QoE is usually done based on aggregating several performance indicators or considering only a single indicator. In [110], the aggregation includes network density, rate of loss of communication packets, and the position of nodes in the network. The model is formalized using aggregate statistics, such as sum of absolute differences, Euclidean distance, and fuzzy interpretation of standard deviation and applied through a multi-step procedure. The outcome of the applied procedure is the delivery of a video to the users during transmissions with low network overhead and high QoE. In addition to [110], [190,119,7] employ aggregate statistics to model QoE. Quadros et al. capture the measurements of human experience using a Structural SIMilarity (SSIM) indicator and a Mean Opinion Score (MOS) [190]. The SSIM measures the structural distortion of a video. Furthermore, the MOS measures the user point of view of video frame sequences per importance. The proposed model is part of a protocol that manages V2V routes of video transmission in real-time. In [119], video bitrate and the monetary cost generated by the traffic through cellular networks, are formulated as a linear programming optimization within a QoE-aware mobile cloud video that can adaptively select the proper wireless interface. Moreover, Aloqaily et al. [7] presented QoE as the weighted sum of the three variables, namely minimizing cost, with the least possible revealed information (privacy) and minimal service latency. The model is adopted within in the concept of SVaaS to provide continuous vehicular services in smart cities. Future service predictions are done using Dempster-Shafer theory and within a QoE Game Model.

A variety of modeling styles are also presented in the literature. The investigation in [214] uses a discrete multimedia model for a buffer-aware QoE Optimization; in addition, it uses power-aware QoE optimization based on power consumption equations. QoE optimization is based on three key sections of multimedia communication in IoV platforms; namely, multimedia communication with the media server, vehicle communications of urgent healthcare data among the vehicles for healthcare through dynamic wireless link and vehicle to healthcare provider data exchange. Furthermore, Hui et al. optimize the QoE of the power grid by maximizing the utilities of aggregators. The proposed optimization is based on contract theory to formulate the problem as an optimization with two classes of constraints then simplifying the constraints by Spence-Mirrlees single-crossing condition. Finally, under regular distribution, the model obtains the optimal contract. In [25], availability, reputation and communication cost are combined to measure the QoE of the task offloading in EC-IoV. The objective is to maximize the overall QoE of a group of users using a double auction process and a resource allocating stage that can be solved with heuristic algorithms. Furthermore, Bozkaya and Canberk formulate QoE in terms of interference in vehicular networks [21]. According to QoE, vehicles are classified as satisfactory or unsatisfactory. Specifically, QoE is quantified as SINR level, which is calculated in terms of transmission power and the interference power of vehicles within the range of each RSU, the noise power, and the path loss at distance d between vehicle and RSU. The authors in [265,215] adopt a single indicator to capture QoE. To that end, QoE is formulated as the peak signal to noise ratio (PSNR) while assessing the performance of video streaming over vehicular networks [265]. Furthermore, Sparrow et al. formulate QoS as the instantaneous packet throughput from the base station to the vehicle; whilst QoE is the additional distance traveled by the vehicle before responding to the command. The proposed formulation is used to examine the balance of QoS and QoE for unmanned vehicles and the implications of providing a secure communication channel during operation.

QoE-specific investigations within CAEVs use a variety of implementation, simulation, and validation tools. The identified tools comprise simulations [214,110,191,262,190,119,7,265,21,25,215] using tools, such as MATLAB [214,21] and NS [110,262,190]. Table 1 presents QoE Models from the literature with their indicators, used evaluation tools, number of received citations, and their mapping to type of vehicle. Innamaa and Kuisma presented in [111] a repository of different indicators for expressing the impact of automation in road transportation in several impact areas. The selected areas comprise use of automated driving, safety, energy or environment, network efficiency, asset management, land use, economic impacts, to name but a few. The study documents the rating results and additional indicators as proposed by 77 experts mostly from Europe, US and Japan. The study further identifies a selection of the most important indicators that are almost all useful in defining QoE aspects.

4.2. Quality of Experience taxonomy

In this section, the developed taxonomy for QoE is presented in the context of CAEVs and abstracted into an extended QoE framework. The proposed taxonomy is based on ten criteria that were carefully developed to cover the wide range of performance aspects of CAEVs.

4.2.1. Criteria and indicators

From the thorough survey conducted on CAEVs in Section 3, all performance indicators that can affect the QoE of CAEVs were identified. Each indicator maps onto a single QoE influencing factor, namely QoS, Human, Context, or Cost. All indicators are then grouped under ten criteria, namely Energy, Security, Networking and Connectivity, Survivability, Subsystem Performance, Safety, Operability, Personal Usability, Travel Efficiency, and Affordability. Fig. 2 presents the proposed taxonomy criteria with sample indicators from each criterion.

Table 1
QoE Models from the literature with their indicators, used evaluation tools, number of received citations, and their mapping to type of vehicle.

Year	Ref.	Model Description	Indicators	Evaluation Tools	Cit. No.	AVs	CVs	EVs
2019	[214]	A discrete multimedia model for QoE optimization	Multimedia communication with the media server; vehicle communications of urgent healthcare data among the vehicles dynamic wireless link; vehicle to healthcare provider data exchange; Power-aware QoE optimization using power consumption equations	MATLAB Simulation	1		✓	
2019	[87]	Mathematical model developed to formulate V2X resource allocation in the presence of multiple cars uploading videos	Utility of the video: transmission rate to maximum server rate ratio	Simulation	9		✓	
2018	[73]	Achieve an optimal QoE with the lowest cost	Logarithmic form of multimedia tasks; price of the resource; cloud processing rate per resource	Simulation	3		✓	
2018	[174]	Access service selection based on social relationship evaluation; interaction time prediction	Pearson correlation coefficient; weighted compositions	Simulation	104		✓	
2017	[7]	QoE framework to provide several vehicular cloud services in a vehicular cloud; future prediction based on Dempster-Shafer theory; QoE game model; minimal service latency based on the weighted sum of three variables	Cost; least possible revealed information (privacy)	Simulation	17	✓	✓	✓
2017	[89]	Use Contract theory to formulate the QoE problem as an optimization; The QoE of the power grid and aggregators can be improved by maximizing their utilities; obtain the optimal contract	Utilities of the power grid and aggregators	None	0		✓	✓
2017	[25]	The objective is to maximize the overall QoE of a group of users who send requests to the access point for task offloading	Availability; reputation and communication cost	Simulation	4		✓	
2016	[40]	Intersection control model: A smoothness metric to quantitatively capture the QoE	Travel time of vehicles when passing the intersection; throughput; fairness; percentage of vehicle jitter; standard deviation of vehicle travel time; vehicle acceleration and expected velocity	Simulation	26	✓	✓	
2015	[191]	The QoE-aware mechanism allows for video dissemination with high quality and low impact from the user's point-of-view; dynamic topology scenarios	QoE-driven unequal error protection; distributed backoff-based forwarding; persistent multi-hop forwarding	Simulation	6		✓	
2015	[110]	Estimation of network status; employ aggregate statistics to evaluate video quality: sum of absolute differences; Euclidean distance; fuzzy logic interpretation of standard deviation; fuzzy logic	Network density; Packet Loss Rate; node's position; motion vectors; image resolution; frame type and size; macroblock details	Simulation; NS-3	6		✓	
2015	[190]	Improve creation and control of V2V routes for live video transmissions; measurements of human experience were carried out with structural similarity (SSIM) and mean opinion score (MOS)	Node failures; important frames of video sequences from the user's point-of-view	Simulation; NS-2	18		✓	
2015	[265]	A mathematical formula that maps QoE to peak signal to noise ratio	Peak signal to noise ratio (PSNR)	Simulation	55		✓	
2015	[21]	Flow Management; Power Management; QoE is proportional to interference in vehicular networks; vehicles are classified as satisfactory per QoE	QoE is quantified as Signal-to-Interference-and-Noise Ratio (SINR) level; transmission power and the interference power of vehicles per RSU; noise power and the path loss between vehicle and RSU	MATLAB Simulation	19		✓	
2015	[215]	QoS is the instantaneous packet throughput from the base station to the vehicle; QoE is the additional distance traveled by a vehicle before responding to a command	Meters; QoS: packets per minute; QoE: meters per second; intermediate number of hops	Simulation	3		✓	

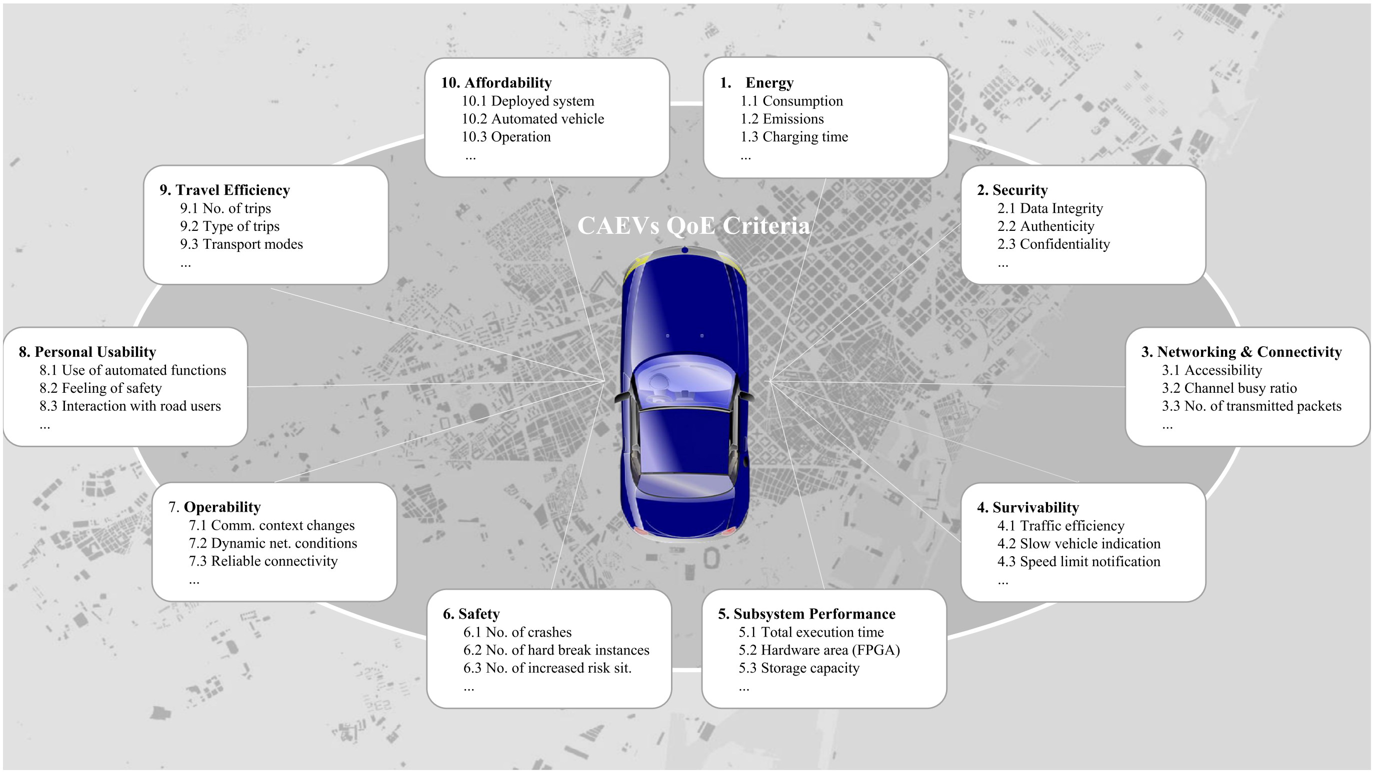

Fig. 2. The proposed QoE taxonomy criteria for CAEVs.

Appendix B presents a set of tables describing the developed QoE taxonomy indicators grouped by criterion. Each indicator is mapped onto one QoE factor, and classified under AVs, CVs, and EVs.

Criterion 1: Energy

Table 4 presents the proposed indicators under Criterion 1. All energy indicators are developed so that they correspond to one QoE factor, which is QoS. A wide range of EV research focuses mainly on studying the effect of EVs on the electric power network. The majority of energy indicators in the literature are used to evaluate the performance of EVs in terms of energy consumption [271,270,60,68,28], vehicles energy emission [135], charging time [19,272,8,19,272], stations availability [266,34,247], battery life [135,19], and energy harvesting [247]. Other energy related performance indicators have been identified in the CV and AV literature such as network transmission power and processing power [219,72,62].

Criterion 2: Security

A major concern within vehicular technology is security. Table 5 shows the proposed security-related performance indicators. All indicators in that table are common for CVs, AVs and EVs, and classified under the QoS factor of QoE. Security indicators include data integrity [49], authenticity [143,49], confidentiality [49], privacy [250,49], and intrusion detection [6,143], to name but a few.

Criterion 3: Networking and Connectivity

Networking and Connectivity is identified as an essential criterion for CVs. A thorough review of CV papers produced the list of performance indicators presented in Table 6. All indicators are classified under the QoS factor of QoE and include service access [219], number of transmitted packets [173], transmission delay [274,210,31,10,92,50], packet delivery ratio [180,273,190], bit error rate [180], communication throughput [180,31,10], degree of mobility [206,209,55], to name a few. Moreover, other indicators are developed to measure network performance in terms of communication bandwidth [87], responsiveness [72], coverage area [62,171], transmission range [219], signal-to-interference-and-noise-ratio [221,21], network capacity [273,77,85], non-outage probability [92], and network lifetime [114].

Criterion 4: Survivability

This criterion relates to various CAEV aspects; the list of proposed performance indicators is presented in Table 7. All indicators are classified under the QoS factor, and used mainly to measure CAEV performance aspects in terms of traffic efficiency [111], speed limit notification [111], parking spot notification [111], cooperative navigation [263,129], and localization accuracy [129,130].

Criterion 5: Subsystem Performance

This criterion describes the performance of CAEV subsystems including Hardware and Software. Table 8 presents the corresponding developed taxonomy indicators. Indicators include the total execution time [56], hardware area in terms of FPGAs and Integrated Circuits resource utilization [56], storage capacity [15], computational complexity [15,47], processing throughput [43] response time [199], fault tolerance [208], processor technology [44], and processor programmability [41].

Criterion 6: Safety

Safety is identified as a critical requirement for CAEVs. This criterion is classified under the Human (Hum) QoE factor. The corresponding proposed taxonomy of indicators is presented in Table 9. The proposed indicators mainly measure the number of crashes and how severe they are (number of fatalities), number of hard breaking instances, number of traffic violations, position tracking level, level of maintaining a constant spacing [229,111]. A significant focus has been identified in the literature on improving the service of disseminating awareness and warning message delivery for CAEVs. This is why the proposed indicators include, among others, perception of safety [126,186,111], information dissemination rate [269,235], cooperation collision warning [145,116,235], wrong way warning [62], traffic jam warning [62], and neighborhood awareness level [116].

Criterion 7: Operability

The operability criterion describes how well the whole system is operating within the context of CAEVs. This is why it is classified under the Context QoE factor. The corresponding identified indicators are presented in Table 10. The indicators include communication context changes [235], dynamic network conditions [235], number of emergency deceleration [111], distance traveled [111], person trip demand [138], truck percentage [228], and vehicle size [135].

Criterion 8: Personal Usability

Personal Usability describes the user's perception in terms of system use and satisfaction during the CAEV experience. This is why it is classified under the Human QoE factor. Table 11 presents the corresponding proposed taxonomy including indicators such as the use of automated functions [111], user's feeling of safety [111], interaction with road users [111], trust [111,152], travel comfort [111], distraction [59], need for training [59], efficient road guidance [116]. Other indicators in Table 11 include psychological gratification [29], convenience [147], navigation system availability [29], and preserving habits of use [29] which are still related to Personal Usability but might not be directly related to the user's experience during the CAEV experience.

Criterion 9: Travel Efficiency

This criterion describes the efficiency of the undergone travel, where all indicators are classified under Context QoE factor (see Table 12). The indicators comprise number and type of trips, transport modes, share of used road types, maximum road capacity, peak period travel time, number of stops, and yaw rate [160,111, 229], among others.

Criterion 10: Affordability

Affordability covers all cost elements affecting both the system and the user. Table 13 presents all the proposed indicators classified under the Cost QoE factor. The identified indicators include the cost of the deployed system [67], operation cost [149], maintenance cost [149], trip cost [149], driver education cost [67], and service charge cost [131].

4.2.2. QoE taxonomy structure

The proposed taxonomy is extensive, comprehensive, and provides a rich menu of KPIs that cover wide CAEV aspects. The proposed QoE taxonomy is a two-level hierarchy tree. The taxonomy groups multiple KPIs per criterion. The structure can be further extended to include mid-tree levels to present Key Performance Measures (KPMs) that can include indicators from one or more criteria as shown in Fig. 3. KPMs combine multiple indicators to capture a specific property or characteristic of interest [46,44]. KPMs enable the customization of various combined indicators that represent QoE and can include one or more KPI. The KPIs can measure quantities or qualities; they can be formulated in equations or even described using scale rubrics [47,44]. The proposed QoE taxonomy hierarchy is scalable, where additional criteria, measures, and indicators can be appended without changing the structure.

The proposed taxonomy enables performance evaluation and supports quality assurance efforts within modern CAEV investigations. For example, a variety of formulation options can be developed to capture QoE including quantitative and qualitative representations—or a combination of both [47,43]. To this end, formulations can benefit from traditional statistical aggregations or machine learning models. Accordingly, QoE classifications can be developed based on multiple-criteria decision making, statistical aggregations, or intelligent classifiers [234,153,122]. Sample indicators that were used to model QoE for CAEVs are shown in Table 1. The indicators can be combined using mathematical formulation as in [214,87,73,174,7,40,110,190,265,21] or other methods [89,191]. Investigations outside the scope of CAEVs that modeled QoE using machine learning include [142,51,9]. Example contextualization of the framework use can consider the Criterion 6, Safety, as a standalone factor contributing to QoE and include all the suggested indicators in Table 9 in its formulation. Another contextualization can combine different criteria, such as Safety (Criterion 6) and Personal Usability (Criterion 8), and a selection of simple indicators from Affordability (Criterion 10) to focus on the human influencing factors and cost within a QoE formulation.

4.3. QoE in CAEVs framework

Based on the proposed CAEVs QoE taxonomy, we believe that sound models should include various aspects that carefully cover all important influencing factors. A model that attempts to capture QoE based on an isolated factor, might lead to inaccurate assessment and evaluation due to neglecting others. For example, formulating QoE purely based on service-related indicators can miss user dissatisfaction due to high cost, unwanted context, or undesirable human situation. In that regard, application designers can best decide on what factors to consider, and accordingly which indicators to account for in their QoE model. In this paper, we propose a generic QoE framework that attempts to integrate the different influencing factors to enable ranking and classifying the attained level of quality. The proposed framework does not include statistical aggregations or mathematical formulations that aim to formulate QoE. However, the proposed framework reasons about important factors' integration aspects that are essential in the later development of a measurement system based on the proposed taxonomy. Example formulations within analytical frameworks are presented in [44,47,43,48]. The ultimate purpose of the proposed framework is its embedding within CAEV applications. Indeed, the surveyed literature includes vast opportunities for integrating the proposed framework. For instance, the work in [181] can benefit from the indicators of Criterion 2, Security, and the proposed QoE framework to develop a model that targets access control within the context of IoT.

The suggested QoE framework is of five main entities. Each entity can be modeled based on a single or combinations of the relevant taxonomy KPIs. Three entities represent the QoS, Context, and Human influencing factors (see Section 2). A fourth entity representing a QoE Cost Model is integrated with the other influencing factors to provide a central QoE Model with inputs based on the taxonomy indicator measurements. To that end, the outputs of the QoE Model can include rankings of QoE and performance level classifications according to a predefined scale of satisfaction (see Fig. 4). Given the output rankings and classifications, recommendations can be given to adapt the embedded CAEV system and enable quality improvements. Moreover, the Context entity represents a fixed factor that cannot be modified based on recommendations, however, options within the Context can be reconsidered. The QoS, or System factor, feeds the QoE Model with the current adopted service and its quality level. Here, the same information is provided to the QoS Cost Model. In addition, the QoS Cost Model provides the QoE Model with details on the current adopted rate of services and other available service options. Based on the output recommendations, the QoS entity provides alternate service options to the Cost Model for pricing. The available alternate QoS options are combined with the information from the Human entity; accordingly, suitable cost options are fed to the

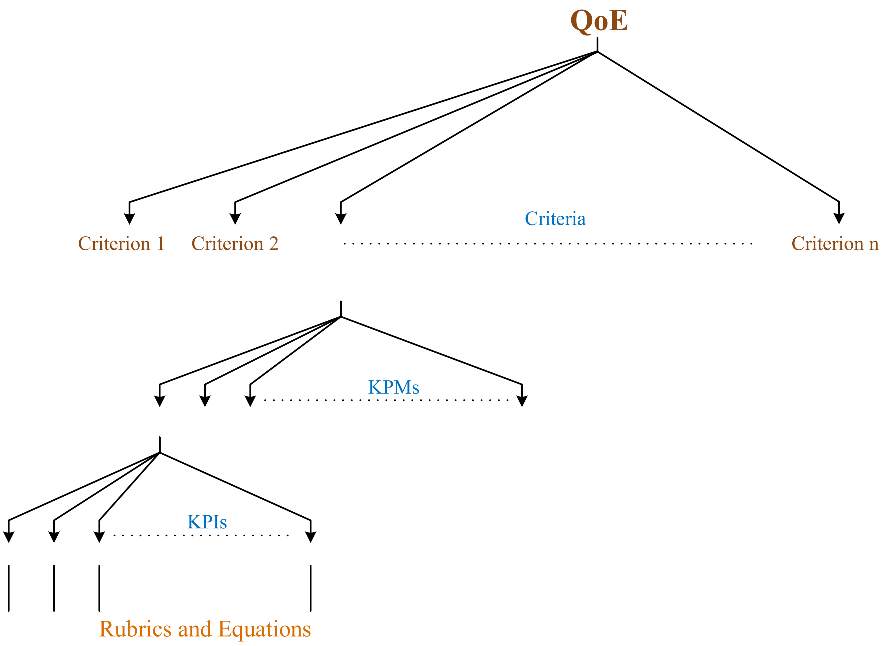

Fig. 3. The structure of the proposed CAEVs taxonomy.

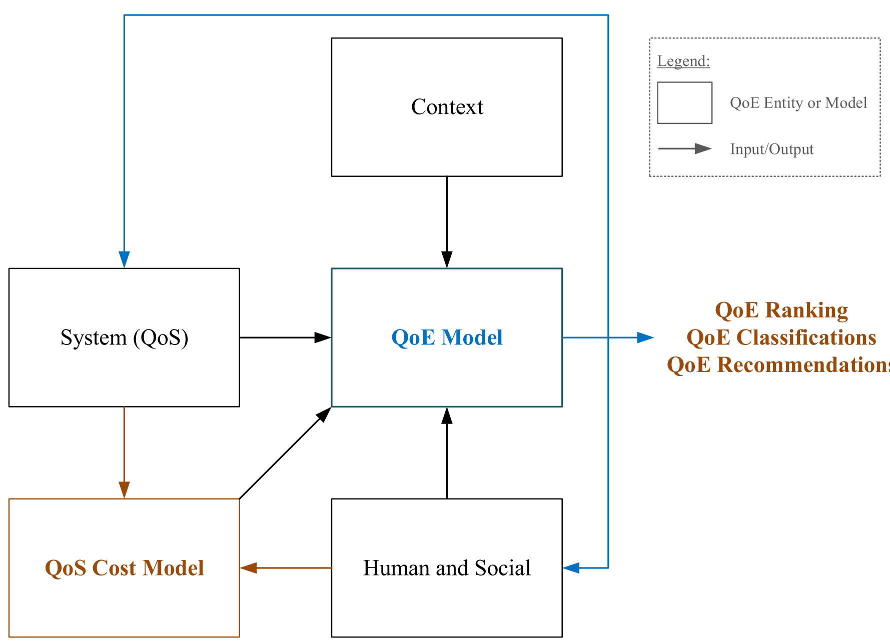

Fig. 4. The proposed QoE for CAEVs framework.

QoE Model for a new service quality ranking and suitable recommendations. Furthermore, the Human entity adapts to changes in human opinion and to new social considerations. Indeed, the QoE Model can be implemented to run in real-time and provide outputs that drive the whole system or enable desired optimizations.

5. Discussion and recommendations

In this section, recent advances are critically appraised, challenges and gaps are identified, and improvements are carefully proposed. The section includes reviewing the main efforts towards CAEVs development by top car manufacturers, identifying open research problems, and identifying area transformation and future trends. In addition, a discussion is presented on various hardware and software implementation options related to important CAEV applications such as ITS and smart cities.

5.1. CAEVs of top manufacturers

In 2017, The International Organization of Motor Vehicle Manufacturers published its annual report on the world motor vehicle production [161]. The reported list of top ten manufacturers, including the number of vehicles produced, is shown in Table 2. A thorough review of the manufacturers' projects on CAEVs reveals the great current interest in such types of modern vehicles. Although all manufacturers recognize the importance of CAEVs, and consider them as the vehicles of the future, differences in the magnitude of initiatives and Research & Development effort are observed.

Table 2
Current CAEVs aspects presented by the top ten car producing manufacturers as per the 2017 ranking [161] and their quality policy.

Rank	Manufacturer	No. Vehicles	CAEV Aspects	Quality Policy
1	TOYOTA	10,466,051	**C:** Care sharing service; emotional bond with driver. **A:** Developing its autonomous driving products under its Active Safety and Automated Driving Development Framework. **E:** A range of EVs to support athlete movement at the Olympic and Paralympic Games Tokyo 2020; Compact and luxury EVs; [232].	"Customer First" and "Quality First [233]"
2	VOLKSWAGEN	10,382,334	**C:** WirelessCar; We Park application. **A:** Developments are on autonomous driving at Level 4. **E:** Electric racing car; EV battery cell assembly; modular electric drive matrix technology; a variety of EVs; [240,241,245,242,244].	Sample strategic goal that highlights customer perception: "We will impress our customers with our outstanding quality by understanding what exactly they perceive as quality and implementing this in our products [243]."
3	HYUNDAI	7,218,391	**C:** Smart traffic jam assistance; interactive voice recognition; remote parking assistance. **A:** Highway driving assistance; augmented reality; night view; motion recognition; driver state monitoring; smart blind spot detection; motion recognition; Auto Link application. **E:** Green cars; a variety of EVs; [93,97,94]	Sample core value: "We promote a customer-driven corporate culture by providing the best quality and impeccable service with all of our effort aimed at satisfying our customers [95,96]."
4	GENERAL MOTORS	6,856,880	**C:** Automatic crash response; emergency services; stolen vehicle assistance; roadside assistance; turn-by-turn navigation. **A:** Cruise LLC; learning ability; cloud-based data; environment data analysis; Webviz visualization of vehicle decisions. **E:** All-electric cars, zero-emissions, zero-congestion, zero-crashes future; transform battery technology; a variety of EVs; [169,38].	"...we're determined to do it again as we redefine mobility to serve our customers and shareholders and solve societal challenges [168]."
5	FORD	6,386,818	**C:** Parking space guidance; traffic light assistance system; tunnel information system; Vario display; traffic control systems; smart traffic sign transmission; bad weather warning. **A:** Investments and collaborations with Velodyne, SAIPS, Nirenberg Neuroscience LLC and Civil Maps. **E:** Battery technology; fast charging; all-electric vehicles; [165,166,162,163].	Indirect and only appears in the vision: "Our aspiration: To become the world's most trusted company [164,187,79,167]"
6	NISSAN	5,769,277	**C:** Alliance Intelligent Cloud. **A:** ProPILOT technology: single-lane, highway-oriented, advanced driver assistance technology; intelligent infotainment systems; safety. **E:** A variety of EVs; [157]	Nissan seeks to provide high quality at all stages of the customer experience through the "Enhancing Quality" program [175].
7	HONDA	5,236,852	**C:** HondaLink; My Honda application. **A:** Honda Sensing: lane keeping assistance, traffic sign recognition, lane watch, blind spot information, cross traffic monitor; industrial collaborations on self-driving technology. **E:** Electrified vehicles; low emissions; easy charging; fuel efficiency; [81,82,33,84].	"Maintaining a global viewpoint, we are dedicated to supplying products of the highest quality yet at a reasonable price for worldwide customer satisfaction [83]."
8	FIAT	4,600,847	**C:** Remote services, stolen vehicle location assistance; voice commands; Apple CarPlay; Android Auto; Eco:Drive. **A:** Efficiency coach; highway assist safety feature; evolutionary technologies. **E:** Battery technology; V2G; [69,156]	"Global Quality through World Class Manufacturing" [70]
9	RENAULT	4,153,589	**C:** Intelligent cloud; traffic safety; smartphone connectivity; Coyote on display; Waze on display; intelligent infotainment systems. **A:** Advanced Driver Assistance Systems; LIDARs. **E:** Fast charging; battery technology; a variety of EVs; [195].	"Your Satisfaction, Our Priority"; [196]
10	Groupe PSA	3,649,742	**C:** Safety through connectivity. **A:** Assisted driving: parking, traffic, driving; seamless and reliable driving. **E:** Clean mobility; battery technology; a variety of EVs; [188].	"Your requirements, our uncompromising commitment" [189]

CAEV units at the top ten manufacturers comprise a variety of interesting connectivity features. Initiatives at Toyota include car sharing services among different users and building emotional bonds with drivers [232]. Recently, Volkswagen took over the telematics specialist WirelessCar from Volvo. Volkswagen Group is using WirelessCar's connectivity technology to drive the development of its digital ecosystem [240]. Moreover, Hyundai, General Motors (GM), Ford, Fiat, and PSA support several features through connectivity. The supported features include smart traffic jam assistance, automatic crash response, emergency services, stolen vehicle assistance; roadside assistance, turn-by-turn navigation, cloud-based data access, tunnel information system, smart traffic sign transmission, bad weather warning, and safety through connectivity [93,97,94,169,38,165,69,156,189]. Furthermore, Table 2 presents a variety of connectivity features presented by the top ten manufacturers.

Besides connectivity, top ten manufacturers are, undoubtedly, on the path towards automated driving. The most part of manufacturers have already embedded autonomy features in their cars, while others have initiated their effort through developments, investments and collaborations. Existing autonomous driving features include highway driving assistance, driver state monitoring, motion recognition, learning ability, visualization of vehicle decisions, intelligent infotainment, traffic sign recognition, automated safety support, and seamless driving (see Table 2) [97,169,163,157,33,156,194,188]. Furthermore, example development effort is made by Toyota under its Active Safety and Automated Driving Development Framework. Toyota aims at eliminating traffic casualties. Sample investments comprise the majority-owned subsidiary of GM, Cruise. Cruise forms the core of GM's self-driving efforts [38]. Moreover, Ford investments and collaborations under autonomous driving include companies, such as, Velodyne, SAIPS, Nirenberg, Neuroscience, and Civil Maps. Ford targets 2021 to build its fully autonomous vehicles [162].

The efforts of top manufacturers towards CAVs appear to be new as compared to their established lines of EVs. All top manufacturers have, or will soon have, their EVs in the market. Toyota, for instance, has developed a variety of compact and luxury EVs. Volkswagen, Hyundai, GM, Nissan, Renault, and PSA now offer several EV models, while the other manufacturers are steadily moving in that direction. The main identified EV aspects of interest at the top ten manufacturers include all-electric vehicles, battery technology, fast charging, easy charging, green cars, to name but a few (see Table 2).

The identified top ten car manufacturers present their commitment to quality in different ways. The presentation shows commitment to quality by all manufacturers, a wide explicit commitment to customer satisfaction among them, while a couple have used terms from the core definitions of QoE. For example, Volkswagen [243], in its group quality management, presented the most QoE-specific in one of its published strategic goals that states: "We will impress our customers with our outstanding quality by understanding what exactly they perceive as quality and implementing this in our products." In a similar attempt, Nissan uses QoE-specific terms to promote their Enhancing Quality Program by claiming that it "...seeks to provide high quality at all stages of the customer experience [175]." The concepts of customers' perception of quality and their experience are, with no doubt, aligned with QoE definitions. Toyota, Hyundi, GM, Honda, Renault, and PSA Group explicitly express their commitment to customer satisfaction (see Table 2). Moreover, Ford Motors aspire to "...become the world's most trusted company." In addition, FIAT calls for "Global Quality through World Class Manufacturing." Quality policies and statements of the top ten manufacturers are listed in Table 2.

5.2. Tesla: the world's best seller

Tesla is the first automotive company which, in addition to manufacturing cars, manufactures solar panels, batteries and other energy related products [193]. Tesla is run more like a tech company than an automotive company [224] by gradually producing until reaching the optimized mass market product [223] and transferring approaches from the technology industry to the transportation industry like updating software packages [216]. In addition, Tesla manufactures totally electric cars. The company aim is to, one day, offer EVs to the average consumer at affordable prices. In 2018, Tesla became the world's best-selling plug-in passenger car manufacturer with a 12% market share [202,201,58] after only ten years in the market. Tesla is different from other automakers in being the only automaker with a high degree of vertical integration [227]. Moreover, Tesla produces its own electric power train components even for electric vehicles of other automakers and deploys its own charging infrastructure. Other automakers outsource typically around 80% of components to suppliers and are not responsible for building gas stations [185].

Tesla is different in its sales strategy where it provides easy online purchasing outlets and in company-owned showrooms. Tesla does not sell its cars through a network of dealers. Tesla also allows its customers to fully customize and order their vehicles online [13]. Even if you visit Tesla showrooms, you are guided to a screen where you can customize your own vehicle and end up with a quote without any hassle or negotiations. Furthermore, Tesla is different in its patents where it allows them to be used by anyone in good faith [225]. Tesla is a community-oriented company committed to bringing jobs back to its local community and hiring underrepresented labor like veterans [90,27,91]. Cumulatively, Tesla sold 921,046 vehicles in 7 years. In May 2015 Tesla started selling refurbished vehicles in the US.

All Tesla vehicles are CAEVs, they are totally Electric and have the ability to be operated autonomously (although the company does not recommend autonomous operation but pitches its autonomous technology as a driver assist rather than autonomous technology) and are connected to the internet over Wi-Fi or other communication technologies. Autonomous aspects of Tesla include Autopilot which includes adaptive cruise control, lane departure warning, emergency braking, Autosteer, Autopark (Parallel and Perpendicular) and Summon [136]. Hardware version 3 comprises eight cameras, twelve ultrasonic sensors, a forward-facing RADAR, two Graphical Processing Unit modules and a driver-facing camera [226,134]. Currently Tesla advertises 7 models, with 3 already in production and 4 unveiled in 2019.

5.3. CAEVs outlook

5.3.1. Pointers to future directions

The extensive CAEVs survey conducted in this paper revealed many interesting aspects related to the main challenges, area transformation, and future directions of QoE. The defined QoE criteria embody multiple aspects and characteristics of CVs, AVs, EVs, and their combined types of vehicles, such as CAVs, CEVs, AEVs, and CAEVs. Several improvements exist for each type. Table 3 presents a summary of the identified pointers to future directions and their mapping to different vehicle types and QoE influencing factors. The identified pointers to future work comprise *improving practical testing* by integrating real road networks, *improving safety*, and *Integrating artificial intelligence and decision support*. Future work investigates the further *Integration of big data and cloud computing aspects* since it allows for better utilization of network resources and more efficient V2I communication. In networking, research efforts can be invested in the *further optimization of resources and performance to satisfy QoS requirements* that can lead to *deploying cost-effective networks*. In the context of EVs, *Developing autonomous energy management* can be done by optimizing the locations of charging stations, integrating intelligent power networks to benefit from idle vehicles, allowing wireless power sharing, and developing removable storage devices to provide fast and safe exchange of energy.

Improving practical testing of CAVs can be achieved by performing urban and transport planning prior to vehicles deployment considering various weather conditions, changes in roadway infrastructure, and parking styles and sizes, to name but a few. *Embedding security features* in CAVs are expected to improve user's experience. This can be done by adapting security algorithms to the context changes or improving secure authentication techniques. Other focus areas for future work could be *improving network effectiveness and speed* within CAVs. This can be done by adopting delay-tolerant network topology and priority queuing mechanisms and providing shared rides.

An effort should be done in *further optimizing QoS taxonomy* in order to insure CAEVs quality. Interesting trending performance indicators include architectural simplifications in terms of system size, portability, and ease of integration. *Integrating artificial intelligence and machine learning within various CAEV aspects* is also a promising area of research for better optimization. Future research

Table 3
Pointers to future work and mapping to different vehicle types and QoE factors. Pointers mapped to all types or all factors are highlighted.

No.	Pointers to Future Directions	CVs	AVs	EVs	QoS	Hum	Context	Cost
1	Improve practical testing	✓	✓	✓	✓	✓	✓	✓
2	Further optimizing QoS taxonomy	✓	✓	✓	✓	✓	✓	✓
3	Integrate AI and machine learning within various CAEVs aspects	✓	✓	✓	✓	✓	✓	✓
4	Develop nonlinear and machine learning models for QoE	✓	✓	✓	✓	✓	✓	✓
5	Improve QoE definitions and frameworks	✓	✓	✓	✓	✓	✓	✓
6	Integrating ICT cross-domain knowledge	✓	✓	✓	✓	✓	✓	✓
7	Improving academia and industry collaboration	✓	✓	✓	✓	✓	✓	✓
8	Involving stakeholders from different industries	✓	✓	✓	✓	✓	✓	✓
9	Developing context awareness	✓	✓	✓	✓	✓	✓	
10	Integrating self-X requirements	✓	✓	✓	✓			
11	Adopting formal development and validation	✓	✓	✓	✓			
12	Applying system architectural simplifications	✓	✓	✓	✓			
13	Use open source tools to reduce cost for customers	✓	✓	✓	✓			✓
14	Identify gaps between industry and policy makers	✓	✓	✓	✓	✓		✓
15	Improving safety	✓	✓	✓		✓	✓	
16	Integrating artificial intelligence and decision support	✓	✓			✓	✓	
17	Integrating aspects of big data and cloud computing	✓	✓		✓	✓	✓	
18	Improving network effectiveness and speed	✓			✓			
19	Further optimize to satisfy QoS requirements	✓	✓	✓		✓		
20	Developing autonomous energy management		✓	✓	✓			
21	Deploying cost-effective networks							✓
22	Optimizing the location of vehicles		✓		✓		✓	
23	Embedding security features	✓	✓		✓	✓	✓	
24	Improve the adoption rate of CAEVs	✓	✓		✓			
25	Attend the needs of pedestrians, cyclists, motorcyclists, and parking	✓	✓		✓	✓	✓	
26	Developing service quality per cost options							✓
27	Integrating social IoT	✓	✓		✓	✓	✓	
28	Design of efficient OS for IoT	✓	✓		✓			
29	Developing interoperability of services	✓			✓			
30	Developing V2G and G2V systems			✓	✓			
31	Improving power harvesting aspects			✓	✓			
32	Developing V2X communication	✓			✓			
33	Hybridizing communication technologies	✓			✓			
34	Adopting 5G features	✓			✓			
35	Developing software-defined networks	✓			✓			
36	Improving network function virtualization	✓			✓			
37	Standardize interaction protocols for AVs and human driven vehicles	✓	✓		✓	✓		

should also concentrate on *improving the adoption rate of CAEVs*. This could be achieved by developing models for their adoption, analyzing response time and calculating fleet operation costs over time. *Attending to the needs of pedestrians, cyclists, and motorcyclists and parking* needs of CAEV users are good areas of future research. Work in this regard should focus on providing personalized online services for each vehicle and equipping vehicles with add-on modules to enable a user to make the best use out of his/her commuting time. *Integrating self-X requirements* in networks of connected vehicles is a must such as abilities of self-healing, self-learning, self-configuration, self-organization, and self-optimization.

Effort can be put on the *development of service quality per cost options* where users can select a set of suitable quality options from a menu of CAEV services depending on their budget. Future research should also focus on *developing nonlinear and machine learning models for QoE* through integrating QoE models with economic parameters (e.g., cost of service) and contextual ones (e.g., time and location). This will help in identifying effective and convenient products and services. Future investigations should also focus on *improving QoE definitions and frameworks*. More effort is needed to integrate QoE aspects related to QoS as well as human and context factors, within the design of CAEV systems or services. It is recommended to widen the QoS related indicators to include, in addition to legacy ones, the correctness of development, level of security and privacy, volume of interoperability and connectivity to the IoV, system safety levels, satisfaction with operation, travel behavior, and passenger mobility.

In addition to the areas of future work stated above, additional opportunities can be identified (see Table 3). These opportunities are expected to help in improving CAEVs performance evaluation and QoE. It is worth noting that a lack of safety standards for CAEVs has been identified, namely in middle-income countries. Hence, more effort is needed in *identifying gaps between CAEVs industry safety standards requirements on one hand and standards set by policy makers on another hand*. Optimizing enforcement of existing road safety laws is expected to make existing roads safer which will, in turn, make the gap smaller between the CAEVs safety requirements and the standards implemented in a country.

5.3.2. Hardware devices for CAEVs

Table 1 reveals that QoE in CAEV investigations widely use tools, such as MATLAB and Network Simulators (NSs), for simulation and validation. CAEVs and their applications, like smart cities and ITS, are built upon implementation and deployment over modern hardware devices. Looking at Tables 4 through 13, it can be noticed that the implementation requirements of CAEVs and their applications range from simple to complex and require hardware devices with varying performance and interfacing characteristics. The variety in requirements of CAEV hardware devices is evident by the presented simulation results and the adopted devices throughout the surveyed literature. As per the identified pointers to future work in Table 3, CAEV hardware devices should enable embedding complex computations and data analytics, security features, integrate social IoT, to name but a few. On the organization level, CAEV hardware devices should support a range of communication technologies and run interoperable and scalable services.

Embedded hardware industries are showing great attention to the requirements of CAEVs and their applications. Currently, ranges of devices are introduced as automotive grade, while others are off the shelf and capable of supporting such a target use. Modern OBUs and RSUs are powerful and can support important ITS applications. An example of modern systems is the DSRC RSUs and

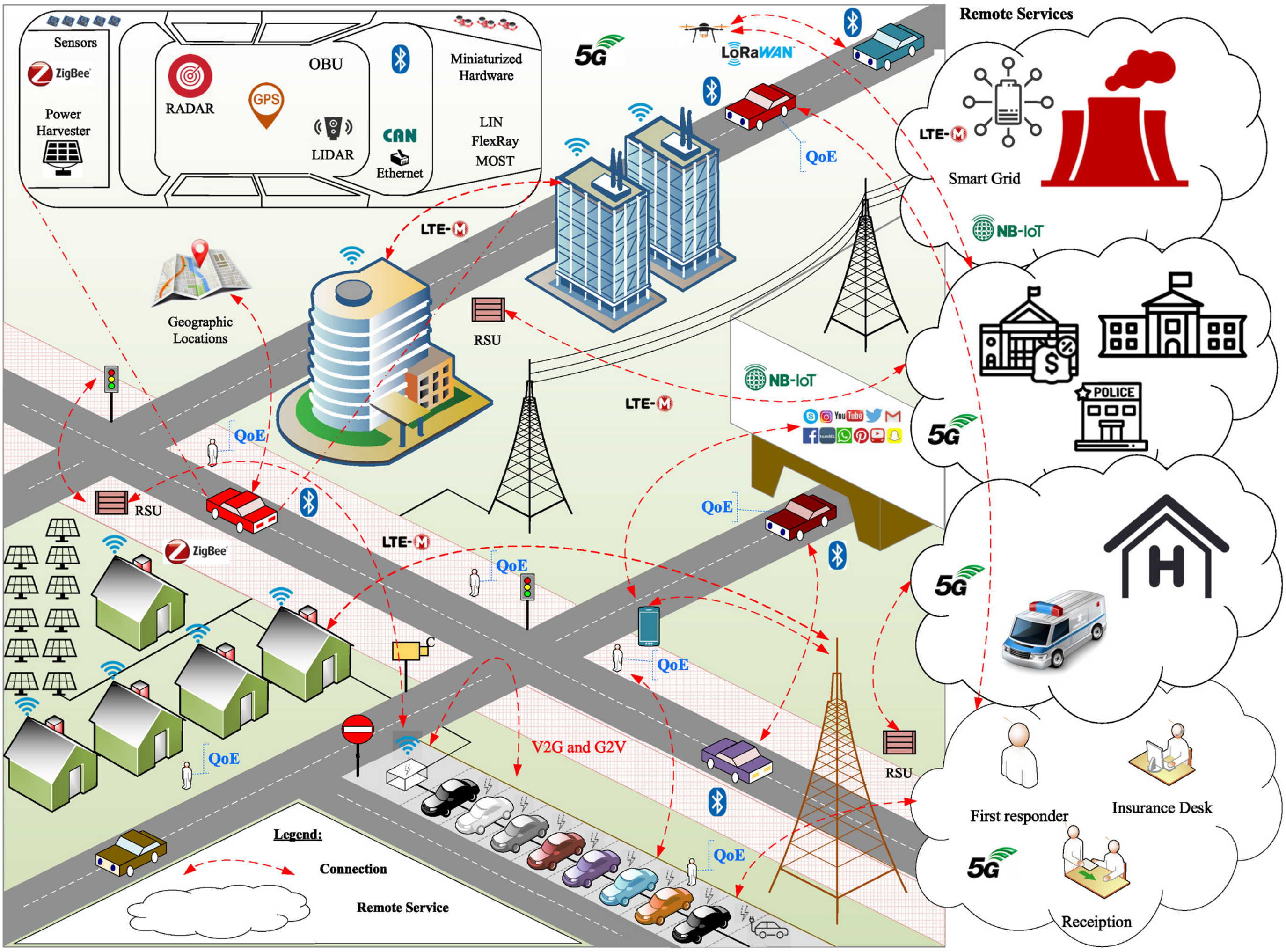

Fig. 5. Future CAEVs deployment in smart cities featuring continuing traditional and future technologies.

OBUs that aim to support applications such as, traffic monitoring, charge of congestion, access and parking system, and enforcement systems. The systems operate around the 5.9 GHz frequency band to communicate securely and consistently between a vehicle and the servicing RSU [63]. In addition, intelligent RSUs are presented in [37]. Many interesting advancements in RSU and OBU architectures are presented in [124,212,238,35,57].

Arduino, Raspberry Pi, and Phidgets are examples of off the shelf hardware components that can be used within CAEVs and their applications. The usual selection criteria of such devices are precision, speed, and programmability. Such devices are easy to assemble and program. In addition, the Microcontroller Units (MCUs) of Arduino provide standardized interfacing layouts. To this end, sensors, cameras, displays, motors, and other expansion boards can be plugged into the larger systems as shields. Recently, Arduino released its plug-and-play tiny Field Programmable Gate Arrays (FPGA) boards that can be connected to a wide variety of industrial vehicular technologies [44]. Furthermore, Microchip released its (MCU)-based CryptoAutomotive Security integrated circuits as the industry's first automotive security development kit [222].

FPGA devices enable rapid prototyping, practical pre-fabrication testing, and efficient implementations of various CAEV aspects. Nowadays, automotive-grade FPGAs are available in the market to support important system requirements, such as, interoperability, modifiability, scalability, and more. FPGA manufacturers are continuously improving performance and increasing gate array capacity. For instance, Xilinx offers reliable and secure technologies to design systems that range from in-vehicle infotainment to automated driving [261].

Graphical Processing Units (GPUs) are extremely powerful and widely used in applications such as autonomous driving. Recently, NVIDIA introduced DRIVE AGX Orin as its highly advanced software-defined platform for AVs and robotics. The platform is supported by a system-on-a-chip that integrates a GPU, Arm CPU cores, deep learning and computer vision accelerators. The platform effectively supports partial through high automation–aka levels 2 through 5 of autonomous driving [36].

6. Conclusion

With the current advancement in vehicular technologies, CAEVs will shape the future of transportation, smart cities, and a wide range of related applications. CAEVs are to provide improved services, increased safety, and cleaner and more sustainable technologies as compared to their traditional counterpart. Today's powerful communication networks, capable embedded hardware systems, and energy harvesting solutions can support different CAEV content that comprise quality transportation system and smart city options.

In this paper, we thoroughly explored the literature for important aspects of CAEVs with focus on performance indicators that can affect the influencing factors of QoE. The survey was extended to cover the main QoE investigations in the literature within CAEVs. To that end, a significantly large taxonomy is developed for QoE within CAEVs that includes 10 criteria and 226 indicators. The taxonomy covered all QoE factors including QoS, human, context, and cost. Furthermore, a framework that captures the relationships among the different QoE factors was proposed to enable integrating QoE in applications within CAEVs. A wide discussion was presented in an attempt to explore the initiatives of top car manufacturers, various modern hardware implementation options, and a large set of pointers to future directions (see Table 3).

As related to QoE within CAEVs, the following research questions remain open for further investigation:

- What mathematical models can accurately capture the proposed QoE indicators?
- What statistical aggregations of indicators can accurately capture QoE and its influencing factors?
- How can qualitative and quantitative indicators be effectively combined to accurately capture QoE in the context of a specific application?
- Which machine learning techniques can best model QoE and its influencing factors?
- What makes an effective framework for QoE assurance?
- How can decision making be made according to multiple QoE criteria?
- How can QoE be integrated in the various aspects of design, implementation, deployment, maintenance, and quality assurance within CAEVs?
- How can QoE be further developed within CAEVs?
- What automotive-grade and off-the-shelf hardware devices are most suitable as implementation options and for what complexity of computations?

In addition, in this paper, several challenges were identified for CAEVs. The first challenge was concerning the privacy of owners and passengers of CAEVs. The exchange of information between CAEVs as well as with roadside devices involves broadcasting information which can be used for other than its intended purposes. The challenge here is to guarantee to CAEVs users that the information is accessible only to its intended audience and that this information cannot be used to violate their privacy. This challenge is exacerbated by another challenge of maintaining good communication between vehicles as well as with other networks for vehicles moving at fast speeds. Another uncovered challenge is to minimize the barriers to adopting CAEVs. The low level of users' trust in autonomous vehicles is still an important barrier to wide adoption of CAEVs. CAEVs are inherently stripping human beings from a lot of control they wielded when they used to drive non-autonomous vehicles. A computer controlling a vehicle without the human being at the helm means that the human being should trust the computer. The non-existence of a human driver is very unnerving to almost all human beings regardless of their technological knowledge. Furthermore, the idea of handing a human's safety to a computer that could be spoofed by a hacker does not help in adoption of autonomous vehicles. A third challenge concerns adoption of CAEVs. Compared to ICEs, CAEVs have a very primitive infrastructure of stations for refilling and shops for maintenance and repairs. Mechanical (moving) parts under the hood have been there for hundreds of years and therefore earned the trust of the consumer. Replacing such moving parts with electric wires is still not acceptable by human users. Furthermore, batteries are still bulkier, more dangerous and have less storage of energy per mile compared to gas tanks. This is also a challenge preventing wide adoption of CAEVs. Finally, the non-existence of effective fail-safe mechanisms which will relinquish control to humans when autonomy fails is another challenge for the CAEVs industry in its quest to replace ICEs.

CAEVs are shaping the future of smart cities and they are expected to significantly cut service availability and costs, promote safety, and reduce transportation associated risks. In the future, CAEVs are to witness increased focus on improving energy harvesting and autonomous energy management. Moreover, future investigations are to tackle important problems related to integrating ICT cross-domain knowledge, hybridizing communication technologies, and embedding security features. As related to the deployment of CAEVs in smart cities, different legacy communication standards are to remain operational in the future, such as, Bluetooth, Wi-Fi, and ZigBee. Moreover, trending technologies like LoRaWAN, IoT-M, NB-IoT, and 5G are to play major roles in enabling CAEV applications. Indeed, assuring QoE in CAEVs can lead to improved service provisions while taking into account user expectations and needs. Fig. 5 attempts to depict future deployments of CAEVs and their enabling ICTs in a smart city. Ultimately, the consideration of QoE in various CAEV investigations creates new opportunities in product development and service providing. QoE as a quality standard goes beyond QoS to include other important influencing factors, namely, human, context, and cost.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. List of acronyms

The acronyms used throughout the article are summarized in the following table.

Acronym	Definition
AEV	Autonomous Electric Vehicle
AI	Artificial Intelligence
AV	Autonomous Vehicle
CAEV	Connected and Autonomous Electric Vehicle
CAN	Controller Area Network
CAV	Autonomous and Connected Vehicle
CIF	Context Influencing Factor
CV	Connected Vehicle
EC-IoV	Edge Computing enabled IoV
EV	Electric Vehicle
FPGA	Field Programmable Gate Arrays
GM	General Motors
GPU	Graphical Processing Units
HIF	Human Influencing Factor
H-CRAN	Heterogeneous Cloud Radio Access Network
ICE	Internal Combustion Engine
ICT	Information and Communication Technology
IoT	Internet of Things
IoV	Internet of Vehicles
ITS	Intelligent Transportation System
ITU	International Telecommunication Union
ITU-T	ITU-Telecommunication Standardization Sector
IMU	Inertial Motion Unit
LiDAR	Light Detection and Ranging
LIN	Local Interconnect Network
LR	Long Range
MOST	Media-Oriented Systems Transport
MCU	Microcontroller Unit
MOS	Mean Opinion Score
mmWave	millimeter-Wave
NS	Network Simulator
OBU	On-Board Unit
PLD	Programmable Logic Device
PSNR	Peak Signal to Noise Ratio
QoE	Quality of Experience
QoS	Quality of Service
QIF	QoE Influencing Factor
RADAR	RAdio Detection and Ranging
RSM	Road Surface Marker
RSU	Roadside Unit
SAV	Shared AV
SINR	Signal-to-Interference-plus-Noise Ratio
SIF	System Influencing Factor
SVaaS	Smart Vehicle as a Service
SSIM	Structural SIMilarity
UWB	Ultra Wide Band
V2C	Vehicle to Cloud
V2D	Vehicle to Devices
V2G	Vehicle to Grid
V2I	Vehicle to Infrastructure
V2P	Vehicle to Pedestrians
V2V	Vehicle to Vehicle
V2X	Vehicle to Everything
VANET	Vehicular Ad Hoc Network
VFC	Vehicular Fog Computing
WeVe	Wearable and intelligent Vehicle

Appendix B. CAEVs QoE Taxonomy

The CAEVs QoE Taxonomy is presented in Tables 4 through 13.

Table 4
QoE Taxonomy Indicators of **Criterion 1: Energy**.

Indicator No.	**Indicator**	**QoE Factor**	**AVs**	**CVs**	**EVs**	**Reference**
1.1	Consumption	QoS			✓	[28]
1.2	Emissions	QoS			✓	[135]
1.3	Charging time	QoS			✓	[8]
1.4	Stations availability	QoS			✓	[22]
1.5	Battery life	QoS			✓	[135]
1.6	Harvesting	QoS			✓	[247]
1.7	Transmission Power	QoS		✓		[62]
1.8	Processing Power	QoS	✓	✓	✓	[135]

Table 5
QoE Taxonomy Indicators of **Criterion 2: Security**.

Indicator No.	**Indicator**	**QoE Factor**	**AVs**	**CVs**	**EVs**	**Reference**
2.1	Data Integrity	QoS	✓	✓	✓	[49]
2.2	Authenticity	QoS	✓	✓	✓	[49]
2.3	Confidentiality	QoS	✓	✓	✓	[49]
2.4	Privacy	QoS	✓	✓	✓	[49]
2.5	Identity	QoS	✓	✓	✓	[49]
2.6	Non-repudiation	QoS	✓	✓	✓	[49]
2.7	Cost overhead	QoS	✓	✓	✓	[49]
2.8	Robustness	QoS	✓	✓	✓	[49]
2.9	Availability	QoS	✓	✓	✓	[75]
2.10	Intrusion Detection	QoS	✓	✓	✓	[143]
2.11	Denial of Service	QoS	✓	✓	✓	[76]
2.12	Transparency	QoS	✓	✓	✓	[119]
2.13	User-driven	QoS	✓	✓	✓	[119]
2.14	Anonymity	QoS	✓	✓	✓	[119]
2.15	Pseudonymity	QoS	✓	✓	✓	[119]
2.16	Unlikability	QoS	✓	✓	✓	[119]
2.17	Unobservability	QoS	✓	✓	✓	[119]

Table 6
QoE Taxonomy Indicators of **Criterion 3: Networking and Connectivity**.

Indicator No.	**Indicator**	**QoE Factor**	**AVs**	**CVs**	**EVs**	**Reference**
3.1	Accessibility	QoS		✓		[142]
3.2	Channel busy ratio	QoS		✓		[140]
3.3	No. of transmitted packets	QoS		✓		[254]
3.4	Packet delivery ratio	QoS		✓		[11]
3.5	Routing control overhead	QoS		✓		[254]
3.6	Transmission delay	QoS		✓		[11]
3.7	Dropped data packets ratio	QoS		✓		[254]
3.8	Bit error rate	QoS		✓		[252]
3.9	Communication throughput	QoS		✓		[11]
3.10	Latency	QoS		✓		[252]
3.11	Communication bandwidth	QoS		✓		[47]
3.12	Received Signal Strength Indicator	QoS		✓		[231]
3.13	Responsiveness	QoS		✓		[72]
3.14	Reliability	QoS		✓		[62]
3.15	Scalability	QoS		✓		[62]

Table 6 (*continued*)

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
3.16	Interoperability	QoS		✓		[67]
3.17	Coverage Area	QoS		✓		[62]
3.18	Jitter in transmission times	QoS		✓		[62]
3.19	Degree of mobility	QoS		✓		[67]
3.20	Communication failure probability	QoS		✓		[146]
3.21	Clustering coefficient	QoS		✓		[250]
3.22	Betweenness Centrality	QoS		✓		[250]
3.23	Average Path Length	QoS		✓		[250]
3.24	Transmission range	QoS		✓		[219]
3.25	Message size	QoS		✓		[206]
3.26	Multiplexing capacity	QoS		✓		[206]
3.27	Data age for vehicles in platoon	QoS	✓	✓	✓	[239]
3.28	Message delivery ratio	QoS		✓		[254]
3.29	End-to-end Delay	QoS		✓		[190]
3.30	Packet Delivery Rate	QoS		✓		[190]
3.31	Packet Loss Rate	QoS		✓		[180]
3.32	Peak signal to noise ratio	QoS		✓		[265]
3.33	No. of RSUs	QoS		✓		[21]
3.34	No. of Vehicles per RSU	QoS		✓		[21]
3.35	Noise Power	QoS		✓		[21]
3.36	Signal-to-Interference-&-Noise Ratio	QoS		✓		[21]
3.37	Total coverage	QoS		✓		[171]
3.38	Average packet reception ratio	QoS		✓		[77]
3.39	Network capacity	QoS		✓		[77]
3.40	Data Block arrival rate	QoS		✓		[140]
3.41	Non-Outage probability	QoS		✓		[92]
3.42	Support	QoS		✓		[142]
3.43	Operability	QoS		✓		[142]
3.44	Coverage lifetime	QoS		✓		[171]
3.45	Retainability	QoS		✓		[142]
3.46	Integrity	QoS		✓		[142]
3.47	System reward	QoS		✓		[210]
3.48	Network Lifetime	QoS		✓		[114]
3.49	Number of services discovered	QoS		✓		[197]
3.50	Service hit ratio	QoS		✓		[197]
3.51	Round trip time	QoS		✓		[55]
3.52	Terminal antenna gain	QoS		✓		[15]
3.53	Terminal receiver sensitivity	QoS		✓		[15]
3.54	Frame delivery ratio	QoS		✓		[18]
3.55	Communication capacity	QoS		✓		[85]

Table 7
QoE Taxonomy Indicators of **Criterion 4: Survivability**.

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
4.1	Traffic efficiency	QoS	✓	✓	✓	[111]
4.2	Slow vehicle indication	QoS	✓	✓	✓	[111]
4.3	Speed limit notification	QoS	✓	✓	✓	[111]
4.4	Parking spot notification	QoS	✓	✓	✓	[111]
4.5	Cooperative navigation	QoS	✓	✓	✓	[111]
4.6	Efficient route guidance	QoS	✓	✓	✓	[111]
4.7	Electronic toll collection	QoS	✓	✓	✓	[72]
4.8	Global Internet services	QoS	✓	✓	✓	[72]
4.9	Multiplayer games support	QoS	✓	✓	✓	[144]
4.10	Roadside Internet access	QoS		✓		[72]
4.11	Localization accuracy	QoS	✓		✓	[116]

Table 8
QoE Taxonomy Indicators of **Criterion 5: Subsystem Performance**.

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
5.1	Total execution time	QoS	✓	✓	✓	[56]
5.2	Hardware area (FPGAs)	QoS	✓	✓	✓	[56]
5.3	Storage capacity	QoS	✓	✓	✓	[15]
5.4	Computational complexity	QoS	✓	✓	✓	[15]
5.5	Processing throughput	QoS	✓	✓	✓	[42]
5.6	Response time	QoS	✓	✓	✓	[199]
5.7	Degree of processor parallelism	QoS	✓	✓	✓	[2]
5.8	Load balancing (work, time, etc.)	QoS	✓	✓	✓	[78]
5.9	Fault tolerance	QoS	✓	✓	✓	[208]
5.10	Redundancy	QoS	✓	✓	✓	[54]
5.11	Storage access time	QoS	✓	✓	✓	[5]
5.12	IO Speed per peripheral	QoS	✓	✓	✓	[203]
5.13	Maintainability	QoS	✓	✓	✓	[208]
5.14	Product and system compatibility	QoS	✓	✓	✓	[258]
5.15	Total execution time reduction	QoS	✓	✓	✓	[208]
5.16	Execution overdue time	QoS	✓	✓	✓	[208]
5.17	Percentage of overdue processes	QoS	✓	✓	✓	[208]
5.18	Assigned per planned resources	QoS	✓	✓	✓	[208]
5.19	Cost of killed/stopped processes	QoS	✓	✓	✓	[208]
5.20	Utilization	QoS	✓	✓	✓	[26]
5.21	Device size and weight	QoS	✓	✓	✓	[260]
5.22	Processor tech. (MCU, PLD, etc.)	QoS	✓	✓	✓	[45]
5.23	Type of communication interface	QoS	✓	✓	✓	[45]
5.24	Processor programmability	QoS	✓	✓	✓	[32]
5.25	Frequency	QoS	✓	✓	✓	[43]

Table 9
QoE Taxonomy Indicators of **Criterion 6: Safety**.

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
6.1	No. of crashes	Hum	✓	✓	✓	[111]
6.2	No. of hard braking instances	Hum	✓	✓	✓	[111]
6.3	No. of increased risk situations	Hum	✓	✓	✓	[111]
6.4	No. of traffic violations	Hum	✓	✓	✓	[111]
6.5	Perception of safety	Hum	✓	✓	✓	[111]
6.6	Cooperative awareness messages	Hum	✓	✓	✓	[235]
6.7	Information dissemination rate	Hum	✓	✓	✓	[235]
6.8	Awareness quality level	Hum	✓	✓	✓	[235]
6.9	Speed Limit Notification	Hum	✓	✓	✓	[116]
6.10	Awareness messages interarrival time	Hum	✓	✓	✓	[235]
6.11	Neighborhood awareness measure	Hum	✓	✓	✓	[235]
6.12	Position tracking level	Hum	✓	✓	✓	[217]
6.13	Cooperation collision warning	Hum	✓	✓	✓	[235]
6.14	Intersection collision warning	Hum	✓	✓	✓	[235]
6.15	Lane change warning	Hum	✓	✓	✓	[235]
6.16	Rear-end collision warning	Hum	✓	✓	✓	[235]
6.17	No. of fatalities	Hum	✓	✓	✓	[111]
6.18	No. of injuries	Hum	✓	✓	✓	[111]
6.19	Improved access to health services	Hum	✓	✓	✓	[111]
6.20	Population exposure to pollution	Hum	✓	✓	✓	[111]
6.21	Quality-adjusted life years	Hum	✓	✓	✓	[111]
6.22	Wrong way warning	Hum	✓	✓	✓	[62]
6.23	Hazardous location warning	Hum	✓	✓	✓	[62]
6.24	Traffic jam warning	Hum	✓	✓	✓	[62]
6.25	Priority vehicle warning	Hum	✓	✓	✓	[62]
6.26	Spacing	Hum	✓	✓	✓	[229]
6.27	Speed difference	Hum	✓	✓	✓	[229]
6.28	Time-to-collision	Hum	✓	✓	✓	[229]
6.29	Queue length	Hum	✓	✓	✓	[229]
6.30	No. of congestion occurrences	Hum	✓	✓	✓	[229]
6.31	Incident Detection Rate	Hum	✓	✓	✓	[186]
6.32	local obstacle avoidance	Hum	✓	✓	✓	[30]
6.33	Availability of legislation	Hum	✓	✓	✓	[179]
6.34	Neighborhood Awareness Level	Hum	✓	✓	✓	[116]
6.35	Safety Awareness Level	Hum	✓	✓	✓	[116]

Table 10
QoE Taxonomy Indicators of **Criterion 7: Operability**.

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
7.1	Comm. context changes	Cxt	✓	✓	✓	[235]
7.2	Dynamic network conditions	Cxt	✓	✓	✓	[235]
7.3	Reliable connectivity	Cxt	✓	✓	✓	[62]
7.4	Delay	Cxt	✓	✓	✓	[256]
7.5	No. of manual control instances	Cxt	✓	✓	✓	[111]
7.6	Control transfer duration	Cxt	✓	✓	✓	[111]
7.7	No. of emergency deceleration	Cxt	✓	✓	✓	[111]
7.8	Min. accepted gap	Cxt	✓	✓	✓	[111]
7.9	Max. acceleration & deceleration	Cxt	✓	✓	✓	[111]
7.10	Speed variation	Cxt	✓	✓	✓	[111]
7.11	Correct use of signals	Cxt	✓	✓	✓	[151]
7.12	Distance traveled	Cxt	✓	✓	✓	[111]
7.13	Variance in journey time	Cxt	✓	✓	✓	[111]
7.14	Vehicle emissions	Cxt	✓	✓	✓	[111]
7.15	Percentage of vehicle jitter	Cxt	✓	✓		[40]
7.16	Situation awareness accuracy	Cxt	✓			[59]
7.17	No. of vehicles on road network	Cxt	✓			[53]
7.18	Available parking spots	Cxt	✓			[53]
7.19	Person trip demand	Cxt	✓			[138]
7.20	No. of detected critical conflicts	Cxt	✓	✓		[228]
7.21	Space between cars	Cxt	✓	✓		[228]
7.22	Vehicle Size	Cxt			✓	[135]
7.23	Truck percentage	Cxt	✓	✓		[228]

Table 11
QoE Taxonomy Indicators of **Criterion 8: Personal Usability**.

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
8.1	Use of automated functions	Hum	✓	✓	✓	[111]
8.2	Feeling of safety	Hum	✓	✓	✓	[111]
8.3	Interaction with road users	Hum	✓	✓	✓	[111]
8.4	Trust	Hum	✓	✓	✓	[111]
8.5	Mental workload	Hum	✓	✓	✓	[111]
8.6	Feeling of ability of control	Hum	✓	✓	✓	[111]
8.7	Feeling of pressure	Hum	✓	✓	✓	[111]
8.8	Ease of use of vehicle	Hum	✓	✓	✓	[111]
8.9	Passenger activities	Hum	✓	✓	✓	[111]
8.10	Distance traveled per day	Hum	✓	✓	✓	[111]
8.11	Travel comfort	Hum	✓	✓	✓	[111]
8.12	No. of journeys	Hum	✓	✓	✓	[111]
8.13	Distraction	Hum	✓	✓	✓	[59]
8.14	Need for training	Hum	✓	✓	✓	[59]
8.15	Video quality over VANETs	Hum	✓	✓	✓	[59]
8.16	Psychological Gratification	Hum			✓	[29]
8.17	Convenience	Hum			✓	[147]
8.18	Screen and keyboard size	Hum	✓	✓	✓	[15]
8.19	User routine and lifestyle	Hum	✓	✓	✓	[15]
8.20	User fairness	Hum	✓	✓	✓	[15]
8.21	Parking spot notification	Hum	✓	✓	✓	[116]
8.22	Efficient route guidance	Hum	✓	✓	✓	[116]
8.23	Roadside internet access	Hum	✓	✓	✓	[116]
8.24	Number of complaints	Hum	✓	✓	✓	[14]
8.25	Customer ratings of service	Hum	✓	✓	✓	[200]
8.26	Maintaining Current Mobility	Hum			✓	[118]
8.27	Navigation system availability	Hum			✓	[29]
8.28	Preserving habits of use	Hum			✓	[29]

Table 12
QoE Taxonomy Indicators of **Criterion 9: Travel Efficiency**.

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
9.1	No. of trips	Cxt	✓	✓	✓	[111]
9.2	Type of trips	Cxt	✓	✓	✓	[111]
9.3	Transport modes	Cxt	✓	✓	✓	[111]
9.4	Share of used road types	Cxt	✓	✓	✓	[111]
9.5	No. of vehicles per hour	Cxt	✓	✓	✓	[111]
9.6	Max. road capacity	Cxt	✓	✓	✓	[111]
9.7	Peak period travel time	Cxt	✓	✓	✓	[111]
9.8	Average travel time	Cxt	✓	✓	✓	[111]
9.9	Total travel time per road	Cxt	✓	✓	✓	[111]
9.10	Median speed	Cxt	✓	✓	✓	[111]
9.11	Free flow speed	Cxt	✓	✓	✓	[111]
9.12	Average parking search time	Cxt	✓	✓	✓	[229]
9.13	No. of stops	Cxt	✓	✓	✓	[229]
9.14	yaw rate	Cxt	✓	✓	✓	[160]
9.15	Stationary wait time	Cxt	✓	✓	✓	[160]

Table 13
QoE Taxonomy Indicators of **Criterion 10: Affordability**.

Indicator No.	Indicator	QoE Factor	AVs	CVs	EVs	Reference
10.1	Deployed system	Cost	✓	✓	✓	[67]
10.2	Automated vehicle	Cost	✓	✓	✓	[149]
10.3	Operation	Cost	✓	✓	✓	[149]
10.4	Maintenance	Cost	✓	✓	✓	[149]
10.5	Trip	Cost	✓	✓	✓	[149]
10.6	Cost of driver education	Cost	✓	✓	✓	[67]
10.7	Service charge	Cost	✓	✓	✓	[131]
10.8	Trade-in value	Cost			✓	[135]
10.9	Cost reduction	Cost	✓	✓	✓	[67]
10.9	Cost of charging	Cost	✓	✓	✓	[19]

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