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AutoLog: Toward the Design of a Vehicular Lifelogging Framework for Capturing, Storing, and Visualizing LifeBits

INAYAT KHAN[1], SHAH KHUSRO[1], (Member, IEEE), NIAMAT ULLAH[2], AND SHAUKAT ALI[1]

[1]Department of Computer Science, University of Peshawar, Peshawar 25120, Pakistan
[2]Department of Computer Science, University of Buner, Buner 19290, Pakistan

Corresponding author: Shah Khusro (khusro@uop.edu.pk)

ABSTRACT Vehicular lifelogging provides us with the opportunity to digitally record life associated with our journeys on the road. Driving on the road is an integral part of life, and it should be given unparalleled attention to log life bits on the road for many purposes, including safety, entertainment, memory augmentation, and analyzing driving behaviors. Various technologies have been used to assist people in capturing live events such as wearable devices, biometric devices, fitness devices, non-visual wearable, and unwearable devices. These devices have played a vital role in capturing the life events of individuals. However, little attention has been given to capturing and recording events related to a person's life on the road. By using a vehicle's integrated sensors along with other auxiliary devices, a vehicle can very conveniently capture personal as well as vehicle-related data of the driver. This research aims to propose a framework, termed as AutoLog, which is implemented in the Android platform and can be installed on any android-based smartphones/tablets or a vehicle's infotainment system. AutoLog is capable of logging the driver activities and vehicle dynamics along with several varying environmental contexts. The proposed solution is evaluated through an empirical study by collecting data from 63 drivers. Different tests, i.e., descriptive tabulation, Cronbach alpha, Kendall's tau-b, and Principal Component Factor Analysis (PCFA) have been carried out to analyze the data. These tests are significant, and the findings show that the use of AutoLog application has a positive perception in terms of attitude, ease of use, user satisfaction, and intention to use. Besides, the findings also prove that the proposed solution helped the drivers in improving risky driving behavior.

INDEX TERMS Vehicular lifelogging, driver behavior, human-computer interaction, memory augmentation.

I. INTRODUCTION

The term Lifelogging refers to the use of computer technologies to capture and store information about a person's daily life experiences in multimedia format for different use-cases [1]. However, the primary goal of lifelogging has been to develop automatic systems to assist human biological memory, especially people with episodic memory impairments. The advancements in capturing, processing, storing, and networking technologies have enabled the development of lifelogging systems to record unobtrusively and passively both lifelog and contextual information without requiring explicit user's efforts and interventions. The lifelogging can be either total capture or selective capture [2]. Total capture lifelogging is the indiscriminate capturing of the totality of life experiences from various sources without having any understanding of use-cases or insights at the outset of lifelogging. Selective capture lifelogging is a domain-focused effort of logging experiences, information about specific aspects, or desired situations of a person with a clear prior understanding of the goals. Technically, lifelogging can be considered as a sub-category of Personal Information Management (PIM). Nevertheless, scope, use of ubiquitous and pervasive technologies, and passive and automatic capturing of the required lifelog data makes lifelogging different from PIM [5].

The lifelogging systems can meet the challenges of enhancing peoples' performances by providing complimentary digital assistance to human memory [3]. Various dedicated lifelogging devices are developed and evaluated by researchers from different aspects. These include wearable

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and non-wearable, type and number of sensors used to capture content and contextual information, processing and storage of captured information, and querying and visualization of the information. The list of dedicated lifelogging devices comprises wearable devices, non-wearable devices, biometrics devices, fitness devices, and non-visual wearable devices. The wearable lifelogging devices are camera-enabled devices, such as SenseCam, OMG Autographer, head-mounted camera, and Go-Pro, etc., which passively capture images of what comes in front of a lifelogger and can be used for memory assistance, healthcare analytics, and lifestyle detection and analysis [4]. The biometric devices sense a lifelogger's body condition and collect information about skin temperature, galvanic skin response, and physiological responses such as heart rate and sympathetic nervous activity. The fitness devices monitor and capture information about a lifelogger's living habits and styles, energy expenditure. The unwearable devices capture information about online interactions, mouse movements, images posts, emails, browser history, etc [5]. Besides these devices, the smartphone is proved as a de-facto lifelogging device due to its technological advancements over the dedicated wearable lifelogging systems [1], [6], [7]. Advanced sensing and computing capabilities make the smartphone an ideal platform for lifelogging [8]. The smartphones-based lifelogging systems exploit the rich sensing capabilities of a smartphone to capture and store content and contextual information to effectively depict a person's daily life activities and events such as places to go, tasks to perform, who to interact with, and what information is consumed, etc. [9]. In short, the lifelogging technologies and tools can effectively capture and store information about a person automatically and persistently and produce personal lifelog archives with varying amount of details including email, documents, photographs, videos, diaries, geodata, music, listening habits, blog entries, navigation history, and web browser bookmarks. The lifelog archives can have potential applications in commerce, government, marketing, social networking, security, and travel [10].

Though researchers have focused on capturing a person's life events with almost every moment, however, little attention has been given to capture information about a person's life on the road. It is essential to record life events of individuals while driving as they are spending a substantial amount of their time in vehicles for journeys and trips. Capturing vehicular lifelog data can provide valuable insights to the life loggers (e.g., in reviewing their past experiences), vehicle owners and drivers (e.g., to identify risky driving behavior), vehicle buyers (e.g., to find out the status of the vehicle including the age of its parts, usage patterns, accidents, etc.), law enforcement agencies for investigation purposes, and friends and family for memory augmentation and contextual recommendations. The latest technological advancements and the integration of sensors can turn vehicles into mobile sensing and computing devices, which could be used for vehicular-lifelogging to log data about environments, contexts, drivers and passengers' activities, etc. [11]. The vehicle lifelog archives could have potential applications and advantages for different stakeholders.

This research paper proposes AutoLog, a vehicular lifelogging framework that addresses common lifelogging challenges. The proposed framework is adaptive, configurable, flexible, and extendible, where the users have the option to manage and configure activities of their interest before logging. The proposed framework, called "AutoLog," can be installed on any Android supported smartphone and vehicle infotainment system and aims to log data about the drivers' activities, vehicle dynamics, and environmental factors, with varying context. AutoLog makes effective use of smartphone and vehicular sensing technologies to capture and identify different driving activities (i.e. cellular communication and other distracting activities), vehicle dynamics (i.e. the speed at a particular time, braking, steering control, engine RPM, etc.), environmental factors (i.e. weather, light, location, noise, etc.), and entertainment such as listening to music and controlling the media player.

The rest of the paper is organized as follows. Related Work is discussed in section II. Section III presents AutoLog design considerations. Data modeling and AutoLog architecture are discussed in section IV and V, respectively. Methods are discussed in section VI, while Results and Discussion are presented in section VII. Finally, this work is concluded in section VIII.

II. RELATED WORK

Various research works have been commenced to assist people for remembering their past events and can be classified into wearable devices, biometrics devices, fitness devices, non-visual wearable devices, and non-wearable devices [5].

Lifelogging literature shows that researchers have presented different lifelogging systems to assist people in remembering their past events and associating them with the current context. For instance, MyLifeBits is a lifelogging tool designed to make annotation of life events easy and fun. It includes text annotation, audio annotation, full-text search, and web browser integration [12], [13]. Similarly, Ubiqlog is a lifelog framework that uses a mobile phone as a lifelogging device to capture and record users' daily life events and provide memory augmentation [7].

The ubiquitous lifelogging systems use embedded sensor technologies (i.e., GPS, microphone, camera, etc.) to automatically sense and record a user's personal experiences [14]. The smartphone is the highly ubiquitous computing device, which combines the features of mobile phones and personal digital assistances (PDAs) [15]. The smartphone integrates a rich set of sensors, computing and processing technologies, and networking technologies, which can be used as a lifelogging device [16]. The benefit of smartphone-based lifelogging is that everyone can carry a smartphone with their selves anywhere. On the other hand, it is very difficult to convince people to carry something other than a smartphone for lifelogging (.e.g., wearable devices [7]). A detailed discussion of smartphone-based lifelogging can be found in [1], [7]. The integration of sensors and latest technologies of contextual rich interfaces and interactions in vehicles have turned vehicles into mobile sensing and computing devices. The strong attachments with vehicles have enabled for the vehicular-lifelogging for several reasons including memory augmentation. Yim and Kim [17] designed a lifelog-based bus information web application which can store the location of the bus where the passenger can easily search the bus. McVeigh-Schultz *et al.* [18] presented vehicular lifelogging system for a MINI countryman, which uses the internal vehicle sensors to alert drivers about ongoing vehicle discoveries, social context, driving environment for the entire life cycle of their vehicles. The memories and sensors specific notification can be displayed on a MINI infotainment system which contains location data, annotated lifelog events and sensors data when a particular location is revisited. In addition, they have developed an iPad based lifelog interface, which assists the users to review the vehicle lifelog events. However, the system is not logging driver specific data (.i.e., phone record, social interaction, driving behavior, etc.) nor providing real-time assistant for vehicle checking and monitoring.

There are varieties of Android applications available in the app market, which captures and visualizes information about vehicle and driving environments [19]. These applications are mostly getting data from OBD device connected with vehicles using Bluetooth technology. One of the most famous applications is the Torque Pro app, which assisting drivers to alert them about their vehicles. The application identifies the problems using OBD color codes and gives information (.e.g., vehicle's performance, temperature, etc.) to the drivers [20]. Another app-based solution called OBDLink is available in the android app market, which facilitates drivers to check trouble codes and diagnose emission and fuel consumption [20]. The OBD eZWay application assists drivers to check fuel statistics, trip statistics, average speed, maximum speed and driving time, etc. The application also shows a safety factor, which can be expressed in points starting from 0 to 100 [20]. The FueLog is an android application, which provides information about fuel consumption, mileage, cost of vehicle and services, etc. The application also calculated statistics like fuel mileage and maintenance expenses [21]. The Car Locator is an android-based application, which provides information about vehicle parking location, which a driver can easily visualize on his/her smartphone. A radar type view can be seen on a smartphone by highlighting the red dot on the map. The application also features like parking timer, ability to store photo and notes, the option to send your current location to another person via email or phone [21]. The SpeedView application uses smartphone built-in GPS sensors and displays information while driving. It provided information regarding vehicle maximum, and average speed, vehicle direction, the total distance travelled, and the remaining time to reach destination [21]. The aCar application is a vehicle management system that assists drivers and vehicle owners by tracking all the important information about vehicle current condition. The information includes fill-ups, gas mileage, maintenance, and trip details [21]. The Car Dashboard provides information about vehicle speed, present vehicle situation, vehicle direction, vehicle current temperature, and vehicle current location [21]. The Beat the Traffic application assists drivers and vehicle owners by providing accurate traffic map available to date while navigating through busy cities. The drivers could access real-time information including average speed, incident on road, road construction, etc. in a locality [22].

III. AUTOLOG DESIGN CONSIDERATIONS

Vehicles by nature are not designed to host and accommodate a huge amount of computation. There are some constraints and limitations, such as resources, interaction, interfaces, etc. in comparison with other computing platforms. The tools used for lifelogging are very privacy-sensitive, which requires proper attention to develop reliable and secure systems. Thus, it is indispensable to examine some design considerations before the implementation of a lifelog application, which will provide grounds for the development of the AutoLog framework.

A. PRIVACY AND SECURITY

Privacy and security are the key concerns for any nature of lifelogging systems [1], [23]. The risks of security and privacy violations could be increased by capturing and sharing excessive personal information in a personal lifelog archive. The vehicular lifelogging could also lead to several privacy and security issues, which need to be resolved for effective logging of information about vehicles and personal experiences. The vehicular lifelogging systems are needed to find answers for the common lifelogging questions such as where to store the lifelog data?; who owns the stored lifelog data?; what could be the lifetime of store data?; who will have to access the lifelog data?; etc. [24]. To tailor with privacy and security concerns, it is needed to define the capturing and recording of fine-grained vehicular lifelogging events and effective methodologies of sharing and visualization.

B. DATA ANONYMIZATION

The important challenge in vehicular lifelogging is what to capture and what not to capture to define clear boundaries for data anonymization [3]. The vehicular lifelogging systems should automatically anonymize lifelog information before recording into a vehicular lifelog archive to conceal the people described by the captured data. However, the automatic data anonymization at capture time could be resource-intensive and requires the development of fine-grained methods. Therefore, the vehicular lifelogging system needs to be designed, allowing lifelogger to have control to manually anonymized capture lifelog data before capturing and should be reversible [25].

C. STORAGE

The fundamental stage of any lifelogging devices is to gather the data in a non-intrusive manner [6], [26].

Lifelogging systems are famous due to the availability of data storages on both local devices and cloud. However, the storage capacity available in the state-of-the-art vehicles is not much enough as compared to personal devices. Vehicular lifelogging systems requires a significant amount of storage capacity to store data such as vehicular sensory data, and video data. [7]. Reading the data from the sensors and other auxiliary devices increases the memory size. For example, a sixteen hours HD video requires approximately 90GB of storage capacity, which is 32TB for one year [27]. Hence, vehicular systems should be optimized to store data intelligently by adjusting device readings.

D. PROCESSING

Bell pointed out in his paper that the future of lifelogging will probably bring us massive storage in less amount of time with limited cost [28]. The capturing devices will never disrupt capturing as the battery power is continuously improving its performance [27]. Similarly, the devices are attached with the dedicated infrastructure, where complex algorithms are running for information retrieval [29]. Vehicular lifelogging systems need to process a huge amount of data for real-time assistance. In order to overcome the processing and storage issues, the vehicular lifelogging system needs to store the events rather than raw data. The vehicular lifelogging system must be intelligent enough to preprocess and filter out the events before storing them into a storage device.

E. SEARCHING AND RETRIEVAL

A lifelog would contain information representing the experiences of both the users and the vehicle for a lifetime. It is not uncommon that a year would be required to review the lifelog information stored in a year. The available solutions, i.e. cluster, indexes, and visualizes lifelog information are using their custom-developed methodologies, especially location, and time information. However, the major challenge is the useful indexing of a large lifelogs for enabling users to retrieve a lifelog segment of their interests. Information retrieval methods have been successfully used for solving semantic memory problems [27]. Therefore, leveraging ideas and experiences from the information retrieval domain in combination with Semantic web indexing and querying technologies can be helpful in fine-grained indexing and retrieval of information from a large lifelog.

F. VEHICLE LIFE CYCLE

All the vehicles are passed through different distinct stages, including the manufacturing stage, operation stage, and end-of-life stages [30]. The research carried out by Polk in 2013 reveals that the average age of a vehicle is about 11.4 years on the road. Based on statistics compiled by Global Market Intelligence Firm R.L Polk & Polk & Co, the average time for changing new vehicles is about 71.4 months means almost six years whereas, for used vehicles, this interval is about 49.9 months [31]. The change of vehicle ownership will lead to challenges in support of vehicular lifelogging systems. Vehicular lifelogging systems aims to record every aspect of life on the road, including personal information, vehicle information, accidents information, journeys, and environmental information. Nevertheless, it would be arduous for the vehicle owners to shift such kinds of information from one vehicle to another if they want to change their vehicle. There should be a facility in vehicular lifelogging systems to obliterate the data from the old vehicle and consolidate it into the new one.

G. LEGAL

The empowerment of individual is the fundamental issue of vehicular lifelogging systems. [32]. The personal lifelogs dataset should be the property of a person who creates them. The Vehicular lifelogging system should be designed in a way that no one records the personal information of an individual without his/her proper permission. The vehicular lifelogging systems need to be customized as it should block lifelog surveillance when an individual is not agreed to log his/her personal information. Furthermore, to provide full control over lifelog data, the owner of lifelogging should be able to delete or add the data [33].

IV. DATA MODELING

AutoLog stores data about each event associated with vehicle life as a data entity. Data modeling is essential for finding patterns in the data stream coming from the list of sensors that best describes the main property of data. For instance, a lifelog dataset is composed of a collection of infinite life events the occurred in a vehicle lifetime. The technologies available in the vehicles enable to capture vehicle information (.i.e., location, speed, temperature, etc.), driver activities information, and environmental/contextual information. Thus, results in a huge lifelog dataset posing threats to the organization, processing, and retrieval. Therefore, a vehicle lifelog dataset is composed of three interconnected sub-datasets: vehicle lifelog dataset, environmental/contextual lifelog dataset, and driver lifelog dataset. The information in the datasets will be stored concerning the driver lifelog dataset.

A. DRIVER LIFELOG DATASET

The driver behavior has been characterized as one of the main reasons for road accidents, mainly due to human errors [34]. To adequately characterize driver behavior and performance, it is vital to log driver activities employing vehicle and smartphone sensors [35], [36]. For instance, the Driver Detection System (DDS) uses smartphone sensors, such as, accelerometer, gyroscope, and microphone, to capture information about driver's movements and smartphone usage while driving [35]. The information about an ith driver lifelog event could be described by the following structure:

$$\mathrm{D}(i) : \{\mathrm{DID}, \mathrm{S}v, \mathrm{S}r, \mathrm{S}s, \mathrm{S}f, \mathrm{S}c, \mathrm{D}c, \mathrm{T}, \mathrm{R}c\}$$

where D(i) represents a particular ith driver lifelog event, DID represents identification of the driver lifelog event, S_v represents information about SMS viewing, S_r represents information about SMS replay, S_s represents information about SMS search, S_f represents information about SMS forward, S_c represents information about searching a contact, R_c represents information about receiving calls, D_c represents information about dialing a call, and T_i represents timing information of a particular event.

B. VEHICLE LIFELOG DATASET

The vehicle lifelogs dataset will record information about vehicle dynamics (i.e., speed, braking status, accelerator, steering wheel) using vehicle and smartphone sensors. The logged information will enable to investigate a driver's driving behavior. The information about an *i*th vehicle lifelogs event in relation to *i*th driver lifelog event could be described by the following structure:

$$V(i) : \{VID, S, T, R, P, CT, T, DIDi\}$$

where V(*i*) represents a particular *i*th vehicle lifelog event, VID represents identification of the vehicle lifelog event, S represents information about speed of a vehicle, T represents information about vehicle throttle, R represents information about vehicle RPM, P represents information about the pressure of vehicle tires, and CT represents information about catalyst temperature, T represent timing information, and DID*i* represents the related *i*th diver lifelog event. The logged data will provide benefits to the drivers while reviewing their driving patterns. For instance, it will be helpful for drivers to investigate the effect of distracting activities on vehicle dynamics.

C. ENVIRONMENTAL LIFELOG DATASET

Logging "life on the road" will provide benefits to the drivers and passengers to recall events related to their journeys such as location, traffic information, weather, noise, music, and direction of the vehicle. AutoLog aims to help support memory for past events. This logged data will act as a timeline where people will review past events related to their journeys. The information about an *i*th environmental lifelog event correlated to the *i*th driver lifelog event could be described by the following structure:

$$E(i) : \{EID, T, W, R, L, M, T_f, D, Tt, DIDi\}$$

where E(*i*) represents a particular environmental lifelog event, EID is the identification of the environmental lifelog event,T represents the environmental temperature, W represents the weather status, R represents the road status, L represents the location of the vehicle, M represents music information at the specific time, T_f represents traffic condition, D represents the direction of the vehicle, T*t* represents the timing information of the event, and DID*i* represents the related *i*th driver lifelog event

V. AutoLog FRAMEWORK

AutoLog [37] has been developed in our lab, which is a novel platform and implemented in several projects including analyzing the risky driving behavior, investigating issues in the existing touch interfaces used by the drivers. The AutoLog platform, as depicted in Figure 1, consists of three main layers, which uses the concept of curating, processing, and insight the data.

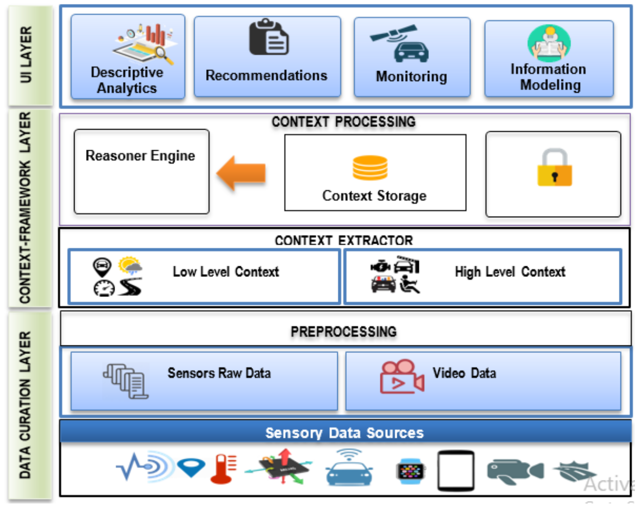

FIGURE 1. AutoLog framework.

A. DATA CURATION LAYER (DCL)

The main objective of the DCL is obtaining, curating, and persevering the data collected from various data sources so that it can further be processed for higher layers. The DCL is divided into sub-modules, such as Sensing and Data Processing. Sensing module uses the vehicular and smartphone sensors along with online data sources to capture the data while processing module is used to process the data.

1) SENSING

The fundamental module in the DCL is sensing the data. The sensing module is composed of sensors and other online sources. Sensors are responsible for sensing the environment, driver and vehicle data in raw format. A sensor can be an application, or it may be separate hardware which can reside physically outside. The AutoLog aims to log driver activities, vehicle dynamics along with environmental context. The driver activities have been identified programmatically using API's and other online sources. Table 1 shows the drivers activities, API's and their descriptions.

Similarly, the vehicle dynamics can be identified through a smartphone, external and vehicular sensors. The vehicular data could be obtained from the Controller Area Network through Onboard Diagnostic (OBD-II) port [37]. The OBD-II ports are available in all vehicles since 1996 that extract information from the vehicle including engine RPM, throttle position, fuel level, fuel ratio, oil temperature, pedal position, catalyst temperature, km/liter, and speed. The vehicle sensors and their description are depicted in Table 2.

Environmental data could be captured using smartphone sensors and online sources. For example, weather information

TABLE 1. Recognizing the driver's smartphone activities.

	Communication				Interactions		
	SMS	Calls	WhatsApp	Email	Voice	Touch	Gesture
Broadcast Receiver	✓	✓	✓	✓			
Speech API					✓		
OpenCV							✓
Keystroke Analysis	✓	✓	✓	✓		✓	

TABLE 2. Vehicle internal and external sensors and their descriptions.

	Speed	Internal Temperature	External Temperature	Throttle Position	Tire Pressure	Door Lock / Unlock	Brake Status	Steering Wheel	Vehicle Status	Passenger Detection
Engine Coolant Temperature Sensor		✓								
Throttle Position Sensor				✓					✓	
GPS	✓									
Temperature			✓							
Switches						✓				
Pressure sensor					✓					
Seat belt sensor										✓
Hand break Sensor									✓	
Pressure sensor for occupant detection										✓
Steering Angle Sensor (SAS)								✓		
Brake Sensor							✓			

could be captured using an online weather API. In AutoLog we have used the OpenWeatherMap[1] API for obtaining the real-time weather updates. Road condition (i.e. rough road and smooth road) has been identified using accelerometer and gyroscope sensors. Environmental sensors and their description are depicted in Table 3.

2) PREPROCESSING

To fulfil the objective of the second module of DCL, it mainly relies on data preprocessing module. The raw sensors data should be preprocessed in a format that is efficient to collect all the sensors readings in one dataset. The Data Preprocessing Module is responsible for preprocessing the sensory data before storing it into the database. Sometimes sensors produce inaccurate data due to noise, power failure, and device failure. To minimize inaccurate readings, low-pass

[1] https://openweathermap.org/api

TABLE 3. Sensors/Applications/Online sources used to identify the environmental parameters.

Sensors/Applications/ Online Sources	Location	Road Condition	Weather	Noise	Traffic Status	Light Condition	Direction
GPS	✓				✓		
Accelerometer Sensor		✓					
Gyroscope Sensor		✓					
Magnetometer Sensor							✓
Light Sensor						✓	
Microphone				✓			
OpenWeatherMap			✓				

filters have been used in order to convert it into a form where events can easily be recognized.

B. CONTEXT FRAMEWORK LAYER (CFL)

CFL is the core layer of AutoLog, which is responsible for processing and storing the contextual information received from DCL. This layer is composed of two main modules, such as context extractor and context processing. Context extractor is responsible for extracting context either low-level or high-level context. The low-level context can easily be recognized without passing through a complex process. The context, for example, location, speed of the vehicle, weather status, can be known as low-level context. However, the context, for example, stay location, traffic status, road condition, can be known as a high-level context. For example, the traffic status can be calculated using sensors fusion (i.e. data obtained from GPS sensors, accelerometer sensors). However, without continuously monitoring these situations, it is difficult to quickly infer whether the road is congested or not. If not implemented carefully, the cost of continuous sensing the context will lead to high resource usage and will need more processing. To overcome this issue, different inferencing rules have been used to infer the context based on available sensors data. Table 4 shows a few rules learned automatically based on available data.

The context processing component is responsible for sensing, processing and storing information extracted from context extractor. Context processing component uses semantic reasoning capabilities based on information modelling and ontological modelling. Reasoner engine is responsible for producing higher-level contextual information by applying rules defined by the user on some set of context data.

C. USER INTERFACE LAYER

The purpose of User Interface Layer is to enrich the overall functionalities of AutoLog through descriptive analytics, implicit recommendations, real-time assistance and comprehensive security and privacy mechanisms. The data obtained from lower layers is very much complex and unstructured and is difficult to understand. Descriptive analytics and visualization modules are responsible for converting the data in such

TABLE 4. Inferred rules based on existing the existing knowledge.

S#	Existing Rules	Inferred Status
1	If (CurrentSpeed<15km/h &&RoadStatus=Smooth && Rain = FALSE && Fog = FALSE	TrafficStatus = "Congested"
2	If (CurrentSpeed<15km/h &&RoadStatus=Smooth && Rain = FALSE &&TrafficStatus = NORMAL	FOG = TRUE
3	If (CurrentSpeed<15km/h &&RoadStatus=Smooth && Rain = FALSE &&TrafficStatus = NORMAL && FOG = FALSE	Incline = TRUE
4	If (CurrentSpeed>=1km/h)	isDriving = TRUE
5	If (Time is Between 7:00PM && 5:00AM)	isNight = TRUE
6	If (isDriving = TRUE && PhoneCall = Received)	SecondaryActivity = TRUE
7	If (noise >=25 decibels)	Environment is Noisy
8	If (LocationVisited Last 5Times)	Known Place
9	If (CurrentSpeed<=30)	Low-Speed = "True"
10	If (CurrentSpeed>=80)	High-speed = "True"

format that human can comprehend easily. The data can be shown in term of analytics and graphs, which will enhance decision making and knowledge discovery.

VI. METHODS

The following sub-section is about the overall procedure adopted for results and analysis of the proposed AutoLog framework.

A. PARTICIPANTS RECRUITMENT

A total of 63 respondents have participated in this study. Among them 30.15% ($n = 19$) female and 69.85% ($n = 44$) were male subjects. The participants were filtered with the condition having a valid driving license and more than three years of driving experience at least. Ages range from 22 to 56 years. The participants were categorized into four different age groups: 22-35 years ($n = 27$), 36-45 years ($n = 21$), and 46-56 years ($n = 15$). The purpose of travel was modelled as business mostly, employee (workplace) mostly, and shopping mostly. The participants purpose of travel: business mostly ($n = 20$), employee (workplace) mostly ($n = 35$), and shopping mostly ($n = 08$).

The reason of small experimental sample size(63) is that we have received almost 200 responses but filtered (dropped) some due to not fulfilling our required criteria. Secondly, the analysis technique applied in this study does not require a specific number of sample size; and as the collected sampled data showed to be consistent and reliable (using Cronbach alpha test), therefore, we have carried further analysis. Thirdly, as the driving behavior in the study area were found to be very similar (based on collected responses), and the results were found conclusive.

B. PROCEDURE AND INSTRUMENTS

The AutoLog implementation aims to demonstrate and evaluate the feasibility of the proposed framework. AutoLog application has been tested on different smartphones of Samsung and LG brands. Figure 2 shows the main Graphical User Interface (GUI) of the AutoLog application, which is followed by a detailed evaluation of the tool on different participants. The AutoLog application runs in the background as a service. However, to ensure privacy in vehicular lifelogging systems, the principles of privacy should be applied. These principles are openness, the participation of individuals, limits of recorded data, data quality, and limits of use. To sustain privacy, we have implemented these guidelines in the proposed AutoLog application, where a lifelogger has access to enable or disable capturing information about their specific activities. For example, if a lifelogger doesn't want some of his/her activities to be logged then he/she may simply disable the option from settings. Similarly, AutoLog will automatically anonymize personal information before storing it on a server.

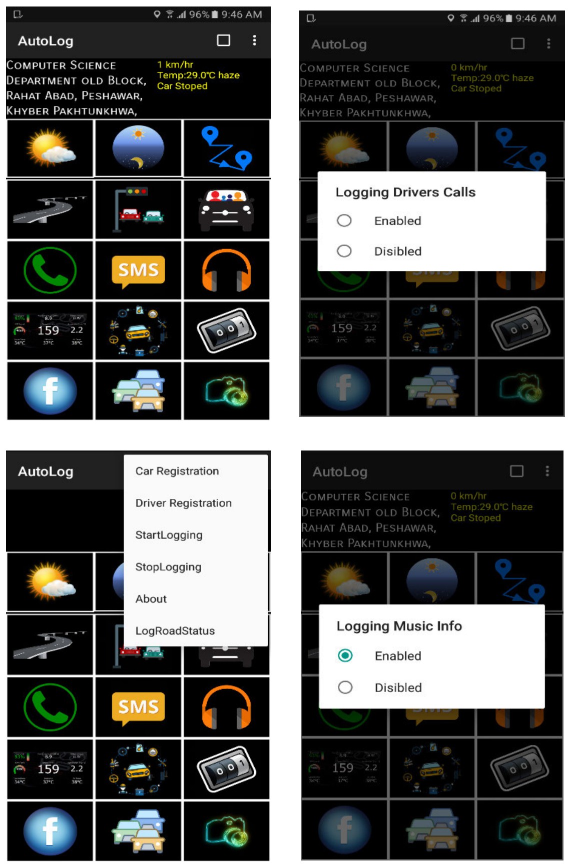

FIGURE 2. AutoLog main GUI screenshots.

To achieve security, we have implemented a strong authentication system in AutoLog application, where a lifelogger has to register himself in the beginning. He/she must log into the system before logging the information about activities. The captured sensitive information (e.g., location, personal phone data) are stored in the internal storage which is more secure as we have set the default file creation mode to "MODE-PRIVATE" in the AutoLog application. The non-sensitive data (e.g., vehicle dynamics and environmental context) is stored and encrypted on the external storage using "Javax.crypto" package.

The AutoLog application has been used by the 63 respondents for a period of three months and has been evaluated through empirical study. We have instructed the participants that AutoLog application will be running in the background to record the driver's smartphone activities, vehicle dynamics, and environmental data. Since the AutoLog needs to be constantly running in the background on the respondent's smartphones while they are driving, it is important to evaluate the power efficiency and storage capacity. The AutoLog is evaluated through the already established parameter and metrics suggested by Human-Computer Interaction (HCI) including attitude, intention to use, ease of use, perceived usefulness, system usability scale, etc. The proposed solution is further evaluated that how much it is successful in augmenting memory and improved driving behavior.

C. DATA ANALYSIS

In this study, we have carried out different tests and analyzed the statistical data using STATA and Excel to investigate the effectiveness of AutoLog application. In our case, we have used descriptive tabulation reporting frequencies and percentages of the categories of the variable. Cronbach alpha measures have been calculated to check data reliability (internal consistency) of the measurement items. All the measurement items (latent variables) are reliable and internally consistent. Further, Kendall's tau-b rank correlation matrix has been calculated to check for multicollinearity, which was found good. Furthermore, we have reported principal component factor analysis (PCFA) and found comparatively better than others.

VII. RESULTS AND DISCUSSION

The following sub-sections are about the overall results obtained from our analysis and their discussion.

A. RESOURCES USAGE EVALUATION

Lifelogging application performance can be measured using five factors, including resource usage, usability, throughput, response time, and reliability [38]. The application evaluation is important for evaluating the implementation of the framework. Since the AutoLog application is running in the background which may lead to resource consumption. Therefore, resources monitoring is a necessary factor before developing any lifelogging application.

1) STORAGE USAGE EVALUATION

Proper management of sensor is the most important factor in lifelogging systems, otherwise the system can instigate other issues such as power, and storage. In our previous research [6] we have built an android app "SAVE" for measuring the effects of sensory data storage capacity while performing daily-life activities in different real-world situations. The collected sensory data of a year gathered and analyzed in Table 5, which discovered that data volume would increase substantially with the passage of time while recording the life events. This growth may lead to storage capacity problems.

TABLE 5. Estimated sensors data volume per year [6].

Sensor Name	Interval		Samples/Second		Volume/Sample in Bytes	Total Volume	
	Minimum	Maximum	Minimum	Maximum		Minimum	Maximum
Accelerometer	0.01 Sec	0.6 Sec	1	102	12	373.248 MB	38.07 GB
Orientation	0.12 Sec	0.6 Sec	1	8	12	373.248 MB	2.98 GB
Magnetic Field	0.12 Sec	0.6 Sec	1	8	12	373.248 MB	2.98 GB
Proximity	Not Determined	Not Determined	0	5	2	0	1.86 GB
GPS	Not Determined	Not Determined	0	1	24	0	746.49 MB
Ambient Light	Not Determined	Not Determined	0	1	12	0	373.24 MB

In contrast, a limited amount of storage capacity will be required to store data related to trips and journeys as the average driving time per day is only 46 minutes [39]. Moreover, AutoLog is vigorously adjusting sensor's reading frequency and time interval based on vehicle current status and variations occurring in the location. A dynamic adjustment would not only minimize the data capacity but also help in lessening battery power consumption.

2) ENERGY USAGE EVALUATION

Lifelogging applications need extreme use of smartphone sensors data, which could affect the battery life. The inadequate battery power of smartphone fosters big challenges for smartphone-based lifelogging applications. Therefore, the sensors are needed to be utilized wisely, else; would result in battery drain quickly. To better assess the consequence of smartphone sensors on battery power, we have developed an Android app and assessed in our previous research [15] to effectively record, monitor, and analyse energy consumption rates of smartphone sensors.

It has been investigated that smartphone sensors, especially the GPS sensor if running continuously will drain the battery very quickly. The smartphone sensors power consumption can be described mathematically as [15]:

$$P_{sensor} = P_{power} \times T_{timeunit} \quad (1)$$

$$P_{sensor}(j) = \sum_{t=1}^{n} P_{sensor}(t) \quad (2)$$

$$P_{data} = (D_{sent} \times T_{timeunit}) + (D_{received} \times T_{timeunit}) \quad (3)$$

$$P_{control} = (C_{sent} \times T_{timeunit}) + (C_{received} \times T_{timeunit}) \quad (4)$$

$$P_{sensor}(j) = \sum_{t=1}^{n} (P_{data}(t) + P_{control}(t)) \quad (5)$$

Equation (1) represents the energy consumed by a sensor P_{sensor} using the energy consumption information specified by the sensor manufacturer for a unit of time. In equation (1), P_{sensor} is equivalent to the nominal power P_{power}, and the time unit $T_{timeunit}$. Equation (2) represents the total power consumed by a sensor in a scenario while the sensor is active. In equation (2), P_{sensor}(j) represents the total energy consumed by a sensor P_{sensor} in a scenario j, that is equivalent to the summation of power consumed by the sensor P_{sensor} in scenario time from 1 to n.

Equation (3) represents the power consumed by a network interface sensor for original data transmission P_{data} that is equivalent to the amount of data sent D_{sent} and amount of data received $D_{received}$ in a unit of time $T_{timeunit}$.

Equation (4) represents the power consumed by a network interface sensor for control data transmission $P_{control}$ that is equivalent to the amount of control data sent Csent and amount of control data received $C_{received}$ in a unit of time $T_{timeunit}$.

Equation (5) represents the amount of power consumed by a network interface sensor P_{sensor} in a scenario j is equivalent to the summation of power consumed by original data P_{data} and control data $P_{control}$ communicated for the duration of the scenario time from 1 to n.

The energy consumption of each sensor is depicted in Figure 3.

On the other hand, AutoLog is dynamically adjusting the sensor readings and uses intelligence if a vehicle stays for more than 10 seconds than the sensors stop sensing until vehicle state changed to driving mode.

3) USABILITY EVALUATION

The AutoLog prototype targets the drivers by providing self-insights about their trips. In order to enable drivers to benefit over AutoLog framework, an AutoLog dataset, as shown in Figure 4, has been visualized to augment drivers their trips, mobile usage and its impact on vehicle speed. As shown in Figure 4 the AutoLog dataset represents the drivers' mobile

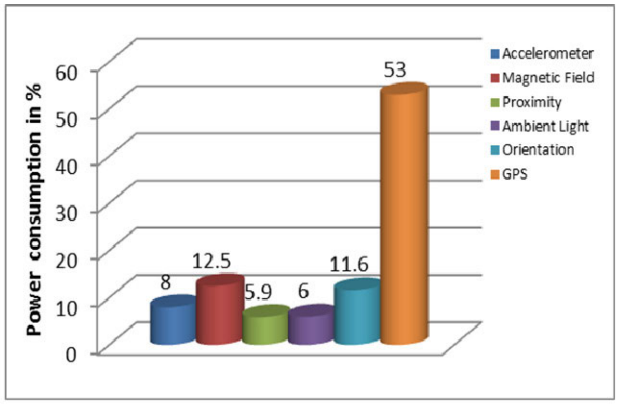

FIGURE 3. Energy consumption of different sensors [13].

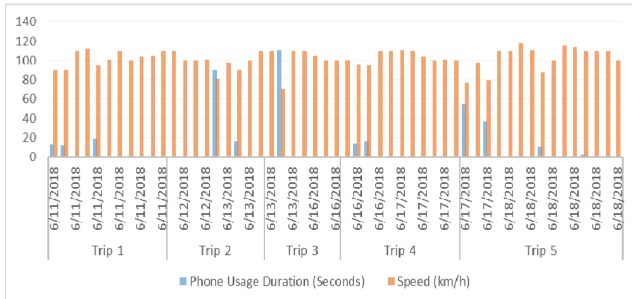

FIGURE 4. AutoLog dataset file represents the driver's trips, phone usage while driving and it's impact on speed.

phone usage with blue bars and speed with brown bars. The speed variations from high to low have been observed when drivers are using their mobile phone while driving.

B. EMPIRICAL EVALUATION

A quantitative study was conducted to collect data from participants for evaluating the AutoLog application. For this purpose, an online questionnaire was completed by the participants about their preferences and usage of AutoLog application and their logging behavior. The questionnaire took approximately 15 minutes to complete, and questions were designed simple and easy to understand. The questionnaire items include driver demographics, questions related to attitude towards usage of AutoLog, intension to use, ease of use, user satisfaction, memory augmentation, and system usability scale. For simplification, the questions in the questionnaire were rating-scales whose answers can be selected from a 5-levels Likert-Scale, ranging from "Definitely" to "Definitely Not".

1) DESCRIPTIVE STATISTICS

The responses of the respondents have been compiled in the following sections and showing descriptive statistics of frequencies and percentages of the categorical indicators of all the variables. About 10 latent variables have been used including an intention to use, attitude, ease-of-use, system usability scale, cognitive load, visual engagement, physical engagement, user satisfaction, augmenting memory, and improving driving behavior. A variable Intention to Use (IU) contains 4 measurement items depicted in Figure 5, showing higher scales, i.e. 4 and 5, which means that respondents are agreed to recommend the use of AutoLog application to others and hope to be used in the future. As shown in Figure 6 the Attitude towards the usage of AutoLog application was positive as most of the respondents selected scales 3, 4 and 5, which means that use of AutoLog is good, beneficial, and interesting.

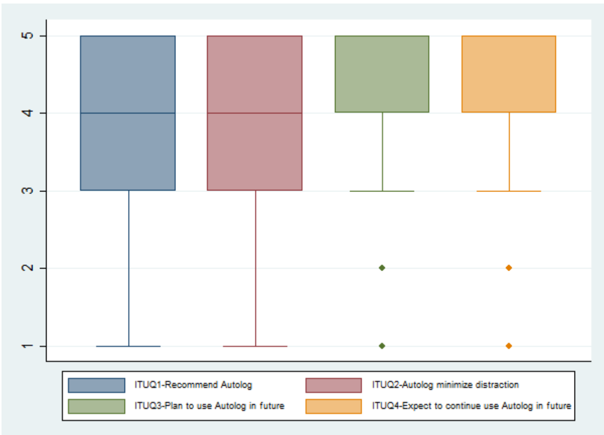

FIGURE 5. Intention to use AutoLog application.

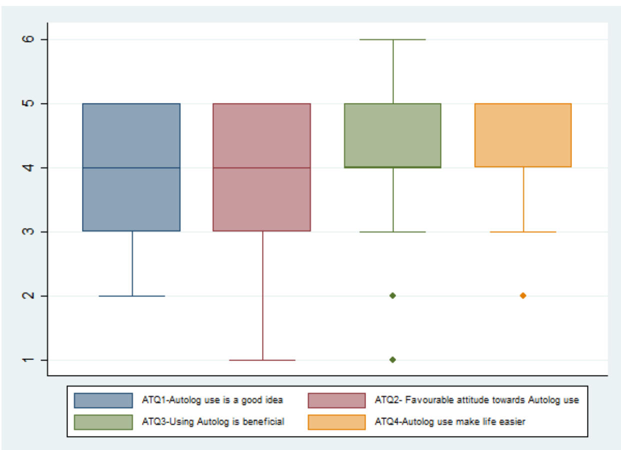

FIGURE 6. Attitude towards AutoLog application.

The respondents' responses for Ease-of-Use were also impressive as depicted in Figure 7, which shows averagely higher scales, i.e. 4 and 5. This means that AutoLog is easy to use, simple, user-friendly, flexible, and consistent. In term of System Usability Scale (SUS), the respondents reported that the AutoLog is not much complex and technically sound application. As shown in Figure 8, most of the respondents reported scale of more than 4.

For cognitive overload, the respondents reported that the use of AutoLog would not increase the cognitive load. Use of AutoLog will not increase the visual and physical interaction as most of the respondent selected scale 3 and above.

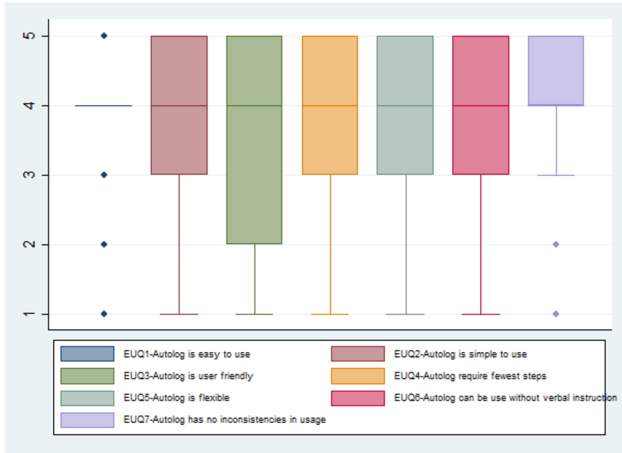

FIGURE 7. AutoLog ease of use.

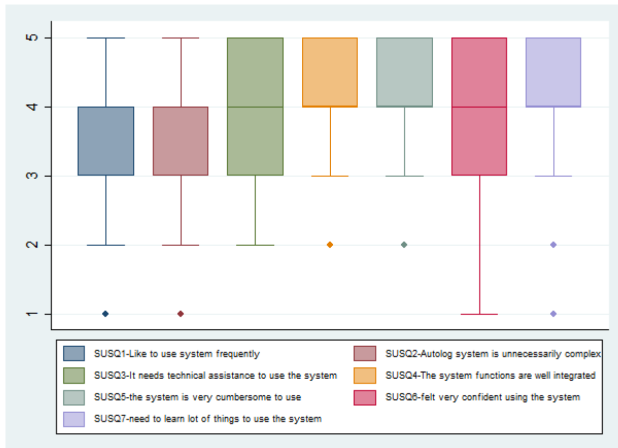

FIGURE 8. System usability scale.

The reason is that the AutoLog application running in the background irrespective of physical and visual involvement. User Satisfaction about AutoLog was high, as reported by a maximum number of respondents with a scale higher than 4 (see Figure 9). In term of memory augmentation, respondents reported that the logged data would recall the memories

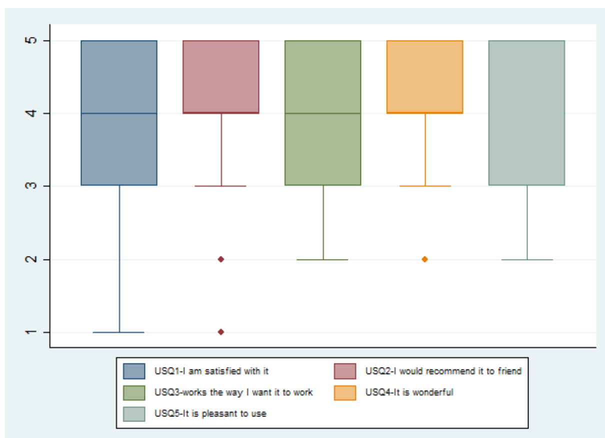

FIGURE 9. User satisfaction.

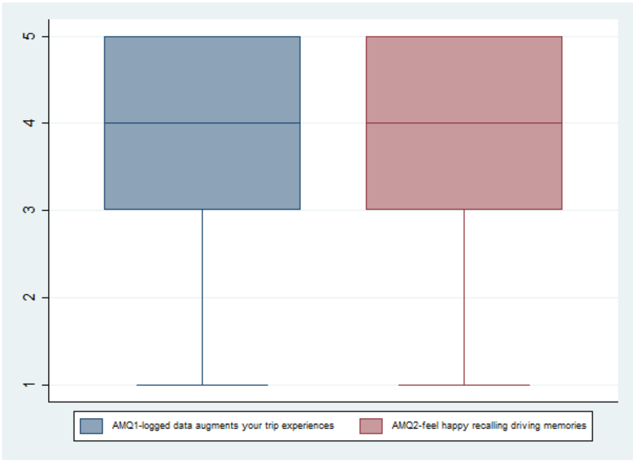

FIGURE 10. Augmenting memory.

related to our journeys (see Figure 10). Finally, the respondents reported that AutoLog would help us to analyze our driving behavior. Similarly, as shown in Figure 11, most of the respondents selected higher scales 3, 4, and 5, it means that AutoLog helped them to identify their risky driving behavior.

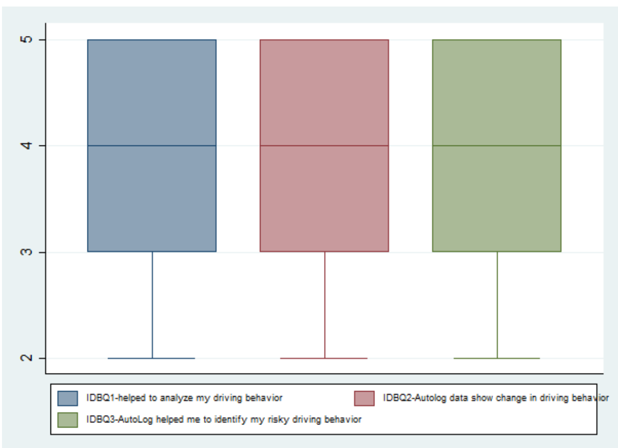

FIGURE 11. Use of AutoLog will improve driving behavior.

2) DATA RELIABILITY AND FACTOR ANALYSIS

The Cronbach alpha test for measurement item's (factors) has been conducted to check the reliability or internal consistency, as shown in Table 6. The alpha scores of all the factors are found reliable as the test scores range from 0.70 and 0.74, which is considered good [40], [41].

As the Cronbach alpha test has a theoretical relationship with the factor analysis [42], we have reported principal component factor analysis (PCFA), considered as most commonly used [43]. The PCFA was found to be more appropriate compared to FA (Factor Analysis), IPFA (Iterated Principal Factor Analysis), and ML (Maximum Likelihood) because of lower uniqueness values showing lower measurement error. The retained factors in PCFA as shown in Table 7 explains the contribution of variation by a particular factor in total variation.

TABLE 6. Data reliability test (Cronbach alpha).

Measurement Items	Observations	Sign	Item-test Correlation	Item-rest correlation	Average Inter-Item Correlation	Cronbach alpha
ITUQ1	63	+	0.5520	0.4809	0.0365	0.7081
ITUQ2	63	-	0.1014	0.0067	0.0423	0.7441
ITUQ3	63	+	0.2815	0.1911	0.0400	0.7305
ITUQ4	63	+	0.2102	0.1173	0.0409	0.7360
ATQ1	63	+	0.5879	0.5205	0.0360	0.7050
ATQ2	63	+	0.3606	0.2741	0.0389	0.7242
ATQ3	63	+	0.3314	0.2433	0.0393	0.7266
ATQ4	63	+	0.1702	0.0763	0.0414	0.7390
EUQ1	63	+	0.1653	0.0714	0.0415	0.7394
EUQ2	63	-	0.0956	0.0009	0.0423	0.7445
EUQ3	63	+	0.2394	0.1474	0.0405	0.7338
EUQ4	63	+	0.0501	-0.0446	0.0429	0.7478
EUQ5	63	+	0.3147	0.2258	0.0395	0.7279
EUQ6	63	-	0.3644	0.2782	0.0389	0.7239
EUQ7	63	+	0.4261	0.3439	0.0381	0.7189
SUSQ1	63	+	0.4280	0.3460	0.0381	0.7187
SUSQ2	63	+	0.2534	0.1618	0.0403	0.7327
SUSQ3	63	+	0.4241	0.3418	0.0381	0.7190
SUSQ4	63	+	0.2337	0.1415	0.0406	0.7342
SUSQ5	63	-	0.1384	0.0441	0.0418	0.7414
SUSQ6	63	+	0.2184	0.1258	0.0408	0.7354
SUSQ7	63	+	0.0973	0.0026	0.0423	0.7444
CLQ1	63	+	0.3179	0.2291	0.0395	0.7276
CLQ2	63	-	0.1104	0.0158	0.0422	0.7434
CLQ3	63	-	0.0324	-0.0623	0.0432	0.7491
VEQ1	63	+	0.1636	0.0697	0.0415	0.7395
VEQ2	63	+	0.0689	-0.0259	0.0427	0.7464
VEQ3	63	-	0.1012	0.0065	0.0423	0.7441
VEQ4	63	+	0.5523	0.4812	0.0365	0.7081
PEQ1	63	+	0.0773	-0.0174	0.0426	0.7458
PEQ2	63	-	0.2309	0.1387	0.0406	0.7344
PEQ3	63	+	0.1028	0.0081	0.0423	0.7440
USQ1	63	-	0.2052	0.1122	0.0409	0.7364
USQ2	63	+	0.2555	0.1640	0.0403	0.7325
USQ3	63	+	0.3198	0.2311	0.0395	0.7275
USQ4	63	+	0.5523	0.4812	0.0365	0.7081
USQ5	63	-	0.1932	0.0999	0.0411	0.7373
AMQ1	63	+	0.2400	0.1480	0.0405	0.7337
AMQ2	63	+	0.3119	0.2229	0.0396	0.7281
IDBQ1	63	+	0.2145	0.1217	0.0408	0.7357
IDBQ2	63	-	0.1442	0.0500	0.0417	0.7409
IDBQ3	63	+	0.3198	0.2311	0.0395	0.7275
Test Scale					0.0403	0.7384

In factors 'Intention to Use, ITU' and 'Attitude, AT', first two factors are retained out of four (Eigen value > 1), but all four factors have Eigen value greater than '0' which can also be considered important factors. The factors 'Ease of Use, EU' and 'System Usability Scale, SUS' have 7 factors each, and PCFA retained 3 and 4 factors, respectively. But again, the Eigen values of all factors are greater than '0' in both factors. The factors 'Cognitive Load, CL'; 'Physical Engagement, PE'; and 'Improving Driving Behavior, IDB' all have

TABLE 7. Principle component factor analysis (PCFA).

Measurement Items	Factor	Eigen Value	Difference	Cumulative	Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
						Factor				
ITU	Factor1	1.33	0.17	0.33	ITUQ1	0.62	0.46	-	-	0.39
	Factor2	1.16	0.37	0.62	ITUQ2	0.68	-0.30			0.43
	Factor3	0.78	0.07	0.82	ITUQ3	0.28	0.78			0.30
	Factor4	0.71	.	1.00	ITUQ4	0.63	-0.48			0.36
AT	Factor1	1.51	0.44	0.37	ATQ1	0.62	0.56	-	-	0.28
	Factor2	1.07	0.16	0.64	ATQ2	0.81	-0.17			0.30
	Factor3	0.90	0.39	0.87	ATQ3	0.42	0.40			0.65
	Factor4	0.50	-	1.00	ATQ4	0.51	-0.74			0.17
EU	Factor1	1.67	0.35	0.23	EUQ1	-0.27	0.03	0.79	-	0.29
	Factor2	1.31	0.25	0.42	EUQ2	0.68	-0.15	0.09		0.49
	Factor3	1.06	0.09	0.57	EUQ3	0.05	0.76	0.08		0.39
	Factor4	0.97	0.17	0.71	EUQ4	-0.44	0.62	-0.26		0.33
	Factor5	0.79	0.14	0.83	EUQ5	0.80	0.13	0.15		0.30
	Factor6	0.65	0.14	0.92	EUQ6	-0.52	-0.45	0.18		0.48
	Factor7	0.51	-	1.00	EUQ7	0.01	0.28	0.53		0.62
SUS	Factor1	1.40	0.09	0.20	SUSQ1	0.78	0.02	0.07	0.01	0.38
	Factor2	1.31	0.16	0.38	SUSQ2	0.60	0.28	-0.18	-0.25	0.45
	Factor3	1.15	0.06	0.55	SUSQ3	0.45	-0.11	-0.67	0.19	0.28
	Factor4	1.08	0.24	0.70	SUSQ4	0.07	0.75	0.11	0.39	0.25
	Factor5	0.84	0.16	0.82	SUSQ5	0.18	0.09	0.34	-0.79	0.20
	Factor6	0.68	0.16	0.92	SUSQ6	0.27	-0.80	0.21	0.16	0.21
	Factor7	0.52		1.00	SUSQ7	0.34	0.02	0.68	0.40	0.25
CL	Factor1	1.12	0.08	0.37	CLQ1	0.80	0.03	-	-	0.35
	Factor2	1.04	0.20	0.72	CLQ2	-0.54	0.67			0.25
	Factor3	0.83	-	1.00	CLQ3	0.44	0.76			0.22
VE	Factor1	1.40	0.39	0.35	VEQ1	0.55	0.33	-	-	0.58
	Factor2	1.01	0.13	0.60	VEQ2	0.73	-0.26			0.38
	Factor3	0.87	0.16	0.82	VEQ3	0.70	-0.30			0.41
	Factor4	0.70	-	1.00	VEQ4	0.26	0.85			0.19
PE	Factor1	1.07	0.06	0.35	PEQ1	0.73	0.22	-	-	0.41
	Factor2	1.00	0.09	0.69	PEQ2	0.73	-0.22			0.41
	Factor3	0.91	-	1.00	PEQ3	-0.01	0.95			0.09
US	Factor1	1.40	0.17	0.28	USQ1	-0.63	-0.19	0.53	-	0.27
	Factor2	1.22	0.16	0.52	USQ2	0.56	-0.58	0.36		0.21
	Factor3	1.06	0.30	0.73	USQ3	0.53	0.54	0.06		0.41
	Factor4	0.75	0.20	0.89	USQ4	0.52	0.30	0.63		0.23
	Factor5	0.54	-	1.00	USQ5	-0.36	0.68	0.48		0.17
AM	Factor1	1.18	0.36	0.59	AMQ1	-0.76	-	-	-	0.40
	Factor2	0.81	-	1.00	AMQ2	0.76				0.40
IDB	Factor1	1.19	0.17	0.39	IDBQ1	-0.78	-0.09	-	-	0.37
	Factor2	1.01	0.22	0.73	IDBQ2	0.73	-0.34			0.33
	Factor3	0.78	-	1.00	IDBQ3	0.18	0.94			0.07

3 factors each and retained two factors, but all factors have contributed to total variation as no factor has negative Eigen values. Similarly, in 'Visual Engagement, VE' two factors out of four are retained, but all factors have contributed to total variation.

In terms of 'User Satisfaction, US', three factors are retained out of five, but all factors have positive Eigen values. The 'Augmented Memory, AM' has two factors, and both have positive Eigen values contributing to total variation.

Kendall's tau-b correlation matrix is presented in Table 8, and almost all of the factors are independent of each other.

TABLE 8. Kendall tau correlation matrix.

	ITU	AT	EU	SUS	CL	VE	PE	US	AM	IDB
ITU	0.56									
AT	0.165	0.605								
EU	-0.002	-0.091	0.497							
SUS	0.081	.06	-0.05	0.302						
CL	0.105	0.077	0.003	-0.01	0.539					
VE	0.060	-0.02	0.046	0.008	0.078	0.623				
PE	0.009	-0.01	0.053	-0.05	0.057	-0.02	0.661			
US	-0.03	0.064	0.064	0.046	0.011	-0.06	0.058	0.396		
AM	0.052	0.103	0.071	-0.02	-0.01	-0.07	-0.04	0.035	0.620	
IDB	-0.06	0.109	-0.08	0.051	0.023	-0.05	-0.01	0.073	0.132	0.437

The independence of the factor's scale (tests) is good showing variation in scales responses of different factors (measurement items) included in the study.

VIII. CONCLUSION

With the emergence of sensors and latest auxiliary technology in vehicles and due to contextual rich interfaces and interaction, a vehicle becomes sensing and computing devices and could be used for vehicular lifelogging. In order to develop a complete vehicular lifelogging system, we need to capture and store the drivers, environment and vehicle dynamics data. It is challenging to deploy highly accurate and reliable physiology platforms in vehicles as they are heavyweight and expensive. In this paper, we have designed and developed an AutoLog application, which is using a smartphone and vehicular sensing technology to identify the driver activities and vehicle dynamics with different varying context. The proposed system aimed to log the events while travelling on the road. The log data will be used for many purposes, including safety, entertainment, memory augmentation, and analyzing risky driving behavior. Furthermore, the AutoLog application was evaluated in real-time by 63 respondents. The approach is evaluated using the different relevant parameters/aspects to show its feasibility and acceptability by the research community and users. The usability of the proposed AutoLog application was evaluated using already established methods, metrics, and usability parameters related to Human Computer Interaction. These usability parameters are: Intention to Use, Attitude, Ease-of-Use, System Usability Scale, Cognitive Load, Visual Engagement, Physical Engagement, User Satisfaction, Augmenting Memory, and Improving Driving Behavior. These parameters are built a Technology Acceptance Model. Technology Acceptance Model determine about how a user can accept a new technology or intervention. We have performed different tests including descriptive tests, factor analysis, and reliability checking. The purpose of these experiments is to investigate the relationship between the user experience attributes of AutoLog usage on the above parameters.

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INAYAT KHAN received the M.S. degree in computer science from the Department of Computer Science, University of Peshawar, Pakistan, where he is currently pursuing the Ph.D. degree in computer science. His current research interest includes the design and development of context-aware adaptive user interfaces for minimizing drivers' distractions. His other research interests include lifelogging, ubiquitous computing, accessibility, and mobile-based assistive systems for the people with special needs. He has published several articles in international journals and conferences in these areas.

SHAH KHUSRO (Member, IEEE) received the M.Sc. degree (Hons.) from the Department of Computer Science, University of Peshawar, Peshawar, Pakistan, and the Ph.D. degree from the Institute of Software Technology and Interactive Systems, Vienna University of Technology, Vienna, Austria. He is currently a Professor of computer science with the Department of Computer Science, University of Peshawar. He regularly publishes his work in reputed international journals and conferences. His research interests include web semantics, web engineering, information retrieval, web mining, search engines, human computer studies, and ICT accessibility. He is a member of IEICE and ACM.

NIAMAT ULLAH received the master's degree in computer science from Quaid-e-Azam University, Islamabad, Pakistan, in 1996, and the Ph.D. degree in information and communication engineering from Inha University, South Korea, in 2013. He served the Higher Education Department, Khyber Pakhtunkhwa, Pakistan, as an Assistant Professor, from 2002 to 2016. In December 2016, he joined Abdul Wali Khan University Mardan (Buner Campus) as an Associate Professor. He is currently an Associate Professor of computer science with the University of Buner, Pakistan. His research interests include wireless communications, ultra-wideband systems, sensor networks, wireless body area networks, and the Internet of Things. He received the Dean's Award in recognition of his excellent academic results and superior research for the Ph.D. degree at the Graduate School of IT and Telecommunications, Inha University.

SHAUKAT ALI received the Ph.D. degree from the Department of Computer Science, University of Peshawar, under the supervision of Prof. Dr. S. Khusro. He is currently a Lecturer of computer science at the Department of Computer Science, University of Peshawar. He has more than ten years of research experience and is an Active Member of the Information and Web Semantics Research (WISE) Group, Department of Computer Science, University of Peshawar. He has authored several research articles published in national and international reputed journals and conferences. He has also attended various conferences and workshops of the national and international levels. His research interests include web semantics, web engineering, information retrieval, ontology engineering, intelligent transportation systems, assistive technologies, and smartphone-based lifelogging for the people with memory impairments.