Development of Drivers' Psychophysiological State Detection Measures and Relevant Machine Learning Methods

Shaima Alameeri
Department of Industrial Engineering and Engineering Management
University of Sharjah
Sharjah, UAE
U19102531@sharjah.ac.ae

Imad Alsyouf
Department of Industrial Management and Engineering Management, Sustainable Engineering Asset Management (SEAM) Research Group
University of Sharjah
Sharjah, UAE
ialsyouf@sharjah.ac.ae

Ahmad Alzghoul
Department of Data Science
Princess Sumaya University for Technology
Amman, Jordan
A.Alzghoul@psut.edu.jo

Hossam Almahasneh
Affiliated member of Sustainable Engineering Asset Management (SEAM) Research Group
University of Sharjah
Sharjah, UAE
hossam.almahasneh@gmail.com

Omar Jaradat
Qamcom Research and Technology
Gothenburg, Sweden
omar.jaradat@qamcom.se

Abdul Kadir Hamid, Anwar Jarndal
Electrical Engineering Department
University of Sharjah
Sharjah, UAE
akhamid@sharjah.ac.ae, ajarndal@sharjah.ac.ae

Abstract

Driver impairment is yet another human factor that is likely to cause dangerous driving behavior (aka distracted driving), leading to safety hazards on the roads. Assuring acceptable drivers' cognitive state can improve safe driving performance. Behavioral and self-report measures are used to assess drivers' cognitive states, but psychophysiological measures can add more considerable value in the real-world driving context. Hence, monitoring, detecting, and responding to drivers' psychophysiological state compose a safety countermeasure that can reduce the risk of distracted driving and thus eliminate or mitigate safety hazards. The research investigates the recent used measures to detect drivers' psychophysiological state, in addition to the drivers' psychophysiological state classification using machine learning. Eye movement, respiration rate, electrocardiogram, electroencephalography, and electromyography are all examples of measures used to deduce drivers' overall psychophysiological state. Tracking and assessing these measures rely on several different metrics, methods, and technologies. For example, drowsiness, as a well-known psychophysiological state, can be assessed and tracked by the eye aspect ratio metric. This paper reviews the recent state-of-the-art measures used for detecting the drivers' overall psychophysiological state. The review considers different psychophysiological states such as fatigue, drowsiness, distraction, and stress. The paper also discusses the strengths and limitations of each reviewed measure, its usage, and its real-time applications. The result showed that the most common used measures are eyes and mouth state measures. Also, several machine learning methods have proven their reliability in classifying drivers' psychophysiological states, especially SVM and CNN as they have wider applications.

Keywords
Driver psychophysiological state, real-time and machine learning.

1. Introduction
Psychophysiological state correlates physiological with human psychological behavior. Psychophysiological measures can be used to assess activity in different body systems (Michaels 1989). Such measures record psychophysiological changes and transform them into an analyzable form. For example, electroencephalography (EEG), electrocardiogram (ECG), electromyography (EMG), eye and face recognition IR trackers (O'Donnell and Hetrick 2016) are used to access fatigue, drowsiness, stress, and distraction (Craig et al. 2011; Rakauskas et al. 2005).

Several findings have represented the negative impact of drivers' psychophysiological state on the driving performance (Haghani et al. 2021; He et al. 2016; Zhao et al. 2021). For example, fatigue is responsible for the death of around 1.35 million individuals annually, according to the World Health Organisation (WHO) (Haghani et al. 2021). Moreover, studies have revealed that fatigued drivers lead to 20-30% of accidents (He et al. 2016). National Highway Traffic Safety Administration (NHTSA) reported in 2014 that drowsiness was the reason behind 846 road accidents (Zhao et al. 2021). Another consequence of accidents caused by drivers' psychophysiological state is that it contributes to financial losses (He et al. 2016). For instance, road accidents cost the Australian economy around 30 billion Australian dollars in 2015 and 33 billion dollars in 2016 (Haghani et al. 2021). Studying the cause and impact of the changes of drivers' states that cause accidents and property loss and consequently find mitigation approaches (Zhao et al. 2021).

According to Rather et al. (2021), a broad classification of drivers' psychophysiological state detection measures groups them into two classes: subjective and objective measures. Subjective measures are influenced by the driver's opinion as questionnaires, while objective measures consider facts such as EEG readings (Lohani et al. 2019). Furthermore, those measures are categorized by their input, including subjective reporting, vehicular characteristics, physical characteristics, biological characteristics, and hybrid characteristics. Subjective reporting mainly focuses on the driver's emotional thinking; responding to certain questions, such as the use of the Karolinska Sleepiness Scale (KSS) (Salvati et al. n.d.). Observing biological characteristics includes heart, brain, skin, and eye signals. Eye state, mouth state, face/head state are all classified under physical treats. In contrast, vehicular characteristics focus on steering wheel angle and lane deviation. Hybrid detection measures combine different features aiming to obtain improved results. Examples of hybrid measures are (1) physical and vehicular, and (2) biological, physical, and vehicular (Rather et al. 2021).

In this paper we aim to review the state-of-the-art of drivers' psychophysiological state detection measures. The scope of this paper focuses on the psychophysiological measures that relate to drivers' fatigue, drowsiness, stress, and distraction. The paper investigates the advantages and disadvantages of the measures used to assess the drivers' psychophysiological state and employability in real-time. State-of-the-art knowledge is reviewed in this paper which includes studies recently. Furthermore, a review of the current machine learning methods and their practices concerning different measures is highlighted in the paper.

The structure of the paper is as follows: Section 2 presents the drivers' psychophysiological state detection measures. Section 3 demonstrates the analysis of drivers' psychophysiological state detection measures. Section 4 presents several machine learning methods that have been used to classify drivers' psychophysiological state. Finally, Section 5 concludes the findings.

2. Literature Review of Drivers' Psychophysiological State Detection Measures

This section presents the revision results on 30 articles related to the measures used to analyze the drivers' psychophysiological state.

Psychophysiological states can be detected through several measures such as EEG, EMG, ECG, percentage of eye closure (PERCLOS), and physical state trackers e.g. face features (Salvati et al. n.d.). Each measure of detecting drivers' psychophysiological state observes specific changes. In addition, each measure has its distinctive advantage and disadvantage. For example, as one of the most used measures, the EEG measures the brain's electrical activity by attaching electrodes to the scalp. The multiple electrodes that obtain EEG signals are highly susceptible to noises from the external surroundings, making it vital to extract informative features to identify driver states accurately (Ren et al. 2021). The most common EEG features detection methods are frequency-domain features and connectivity features. The frequencies of EEG signals (delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) bands) are used as indicators to the changes of driver's cognitive state including distraction, stress, mental fatigue, and drowsiness. However, the EEG has poor spatial information with a frequency-domain approach. Hence, hybrid measures with the frequency-domain are used to overcome this drawback, such as Partial Directed Coherence and inter/intra connectivity approach (Wang et al. 2020). It is noticed that the placement of EEG sensors in real-world applications is not an easy task and causes discomfort or distraction to the driver (Bamidele et al. 2019).

EMG detects the electrical activity produced by the muscles (Rather et al. 2021). Surface EMG (sEMG) sensor is a detachable sensor that can be placed on the vehicle's steering wheel. This sensor has direct contact with the exposed skin of the palm and fingertips of the driver while driving. It is considered a practical non-intrusive way of detecting drivers' psychophysiological state. However, this measure suffers from several drawbacks. For example, if the sensor was placed in the seat's cushion, then there is a specific requirement of the drivers' cloth thickness, which should not exceed 2 mm. Moreover, sEMG signals can be lost or distorted due to the hand movement of the driver. The driver cannot be forced to hold the steering wheel constantly. Finally, each driver has his way of holding the steering wheel, which requires a study of each individual to exactly consider where to place the sensor for each driver (Lu et al. 2021). Measuring the drivers' grip force on the steering wheel is also a part of the EMG measure that is used to detect the drivers' state. Previous studies have found that the driver shifts from conscious to non-conscious or fatigue state after prolonged driving leads to a relaxed grip on the steering wheel. In extreme fatigue scenarios, a driver would no longer hold the steering wheel. This measure is considered a low-cost method for detecting drivers' psychophysiological state as it uses a flexible strip-shaped pressure sensor attached to the vehicle's steering wheel. Moreover, to ensure complete contact of the hands with this sensor, the sensor can be placed on both sides of the steering wheel. This measure has proven its efficiency in recording the grip pressure in actual driving scenarios (Li et al. 2021). However, according to the same reference, certain limitations were endured by the experiment. For example, many subjective features such as handedness (right or left), gender, age, hand positioning, or driving style might have different gripping force strengths.

Many studies as Lim et al. (2020) and Zhongwei et al. (2021) have focused on the facial features to detect the drivers' psychophysiological state. Mainly, the facial features concentrated on the eyes and mouth states such as blinking and yawning. Some research focused only on the eye state (Ryan et al. 2021), while others combined both eyes and mouth (Rathi et al. 2021). The main advantages of such a measure are the easy installation, easy implementation, non-contact, and non-intrusive (Rathi et al. 2021; Zhuang and Qi 2021). An apparent disadvantage for the eyes and mouth state detection is the lower accuracy of detection under face occlusions such as wearing a mask or eyeglasses. Moreover, such measures have lower accuracy during the night, which is the most critical time to detect a driver's tiredness where this system depends on the machine vision technology (Dong et al. 2021) as it is affected by the surrounding brightness (Ren et al. 2021).

Drivers' fatigue, drowsiness or distraction can be detected using eye indicators such as eye aspect ratio (EAR), eye blinking duration, PERCLOS, eye status recognition (open or closed), red eyes, longer duration of closed eyes (Boucetta et al. 2021; Lim et al. 2021; Nosseir and El-sayed 2020; Quddus, Zandi et al. 2021; Ryan et al. 2021; Travieso-González et al. 2021; Victoria and Mary 2021; Xiang et al. 2021; Xue-Da SHANG 2021). Usually, mouth features are combined with eye features to ensure drivers' psychophysiological states. Mouth features include yawning frequency, mouth opening ratio, mouth state, mouth aspect ratio (MAR), and Open Mouth Rate (OMR) (Chen at al. 2021; Li et al. 2021; Li et al. 2021; Liu et al. 2020; Rathi et al., 2021; Valsan et al. 2021; Wang and Qu 2021; Wei et al. 2021; Zhao et al. 2021; Zhongwei et al. 2021; Zhuang and Qi 2021).

According to Dong et al. (2021), respiration and heartbeat signals can be used as aid detection measures to avoid some of the eye detection measures' failures. Respiration and heartbeat signals can be measured by millimeter-wave radar placed in front of the driver by 50 to 80 cm that transmits a signal reflected on the drivers' body to produce an echo signal that is received back again by the radar front end. The echo signal consisting of the amplitude and frequency of the biological signal of respiration and heartbeat is used as an indicator to develop a measure for psychophysiological states detection.

The ECG is another non-intrusive measure for detecting the variability of the heart condition including HRV and HBR of the drivers' psychophysiological state. The HRV indicates the heart rate variability and the HBR indicates the heartbeat rate per minute. They are used as indicators for measuring stress, fatigue, and unconsciousness. A more regular heart rate can be obtained from a concentrated person. On the contrary, the heart rate becomes more irregular and HRV rises when a person lacks attention. The HRV and the PERCLOS experimented and showed similar results as concluded by (Salvati et al. n.d.). This measure has advantages in which it allows constant and non-contact monitoring as it can be embedded in the seatback or at the seat belt. Also, it is not affected by the environmental aspects or face occlusion such as brightness or wearing glasses. Valsan et al. (2021) had used HBR, foot galvanic skin response (FGSR), and hand galvanic skin response (HGSR) to extract psychophysiological features, i.e., stress. Those measures proved to be beneficial and convenient for stress detection as the signals can be obtained through a wearable device. However, while using ECG measures, many sensors must be used to ensure accuracy and signal acquisition quality.

This paper considers a wider scope for detecting the drivers' psychophysiological state than Rather et al. (2021). This is because we consider fatigue, drowsiness, distraction, and stress, and not only fatigue and drowsiness. This paper, however, focuses mainly on drivers' psychophysiological state without looking into subjective reporting or vehicle characteristics detection measures.

3. Analysis of Drivers' Psychophysiological State Detection Measures

This section demonstrates the investigations of psychophysiological measures and their practices in real-time applications. Recent 30 articles were obtained from Scopus.

An analysis of the number of occurrences of each measure was determined to detect the frequency and observe the most common measures during this period as shown in Figure 1. Most of the articles have used eye and mouth states to detect the drivers' psychophysiological state, i.e., 11 out of 30 articles, in which EAR and MAR were the most dominant. Nine articles (30%) considered detecting the eyes state only. Whereas for the EEG measure, four articles utilized it. Other measures such as sEMG, HRV, grip force and HGSR - FGSR – HBR are found only once during this period.

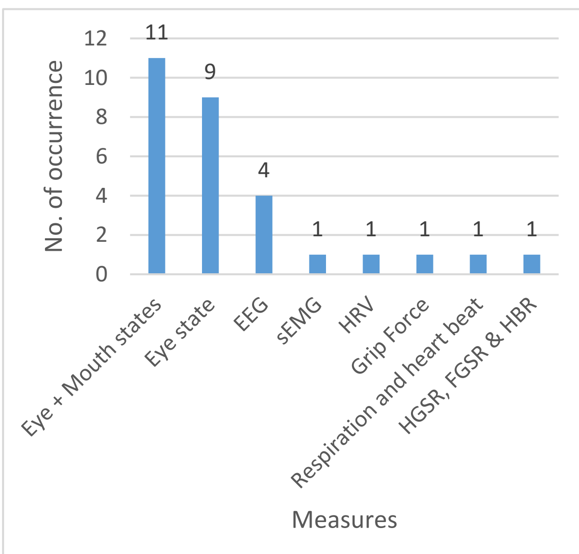

Figure 1. Measures frequency.

As shown in Figure 2, findings revealed that 53.3% of the studies were conducted in real-time (i.e., the data is collected and analyzed immediately). Where 40% of the studies were conducted in offline. And 6.67% were conducted both real-time and offline experiments.

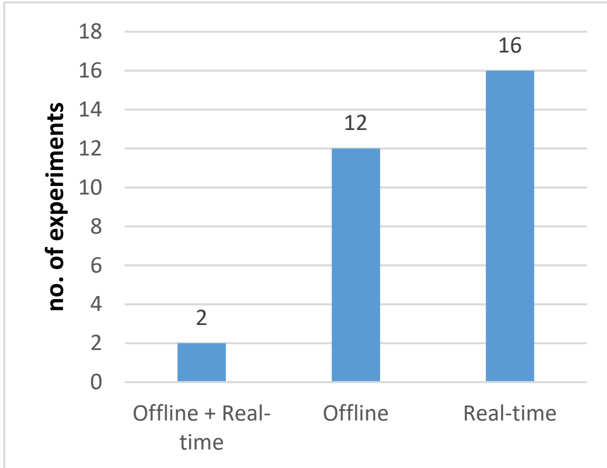

Figure 2. Measure's application.

Through the analysis, it was observed that the covered articles used real-time detection application; while using sEMG, HRV, grip force and respiration with heartbeat measures. However, with HGSR, FGSR & HBR measures, an offline method was utilized. EEG measure was applied only once in real-time experiments as shown in Figure 3. By observing the eye state measure in Figure 4, five experiments used real-time detection and one used both real-time and offline methods while the remaining three experiments were in an offline application. An equal amount of five numbers of experiments were conducted in real-time and offline while detecting eyes and mouth states, and only one scenario used both as demonstrated in Figure 5.

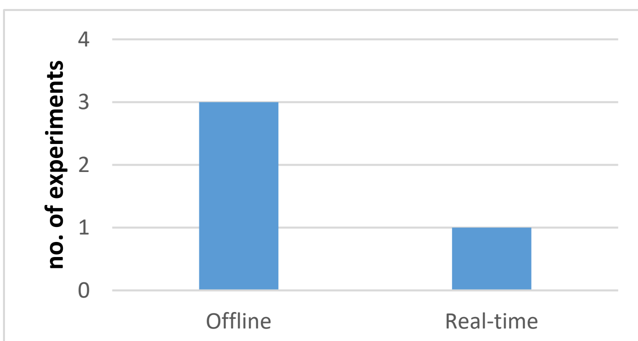

Figure 3. EEG based applications.

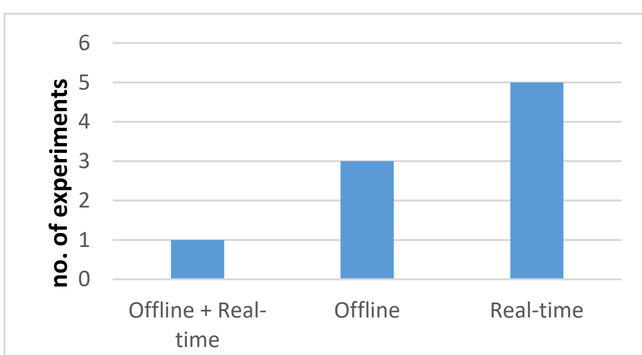

Figure 4. Eye state based applications.

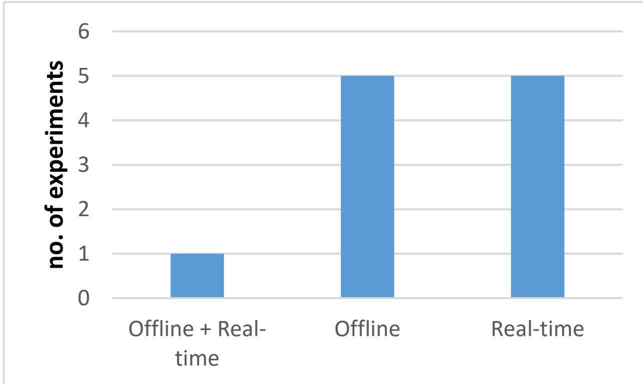

Figure 5. Eye and mouth state based applications.

4. Machine Learning Methods to Classify Drivers' Psychophysiological State

Drivers are responsible for many lives, which could be lost, or people injured, if the drivers are not in their right psychophysiological state. Technological advancement especially in Machine Learning (ML) has introduced sophisticated detection measures to help analyze drivers' psychophysiological state. ML technologies such as support vector machine, convolutional neural networks, logistic regression, etc., show great prospects in classifying the detection measures.

Support vector machine (SVM) is a supervised learning method (Xie et al. 2018) that is efficient in the classification and recognition of patterns (Karamizadeh et al. 2014). It has a wide range of usage especially in face and image recognition, speech recognition and text categorization. In addition, the method has proven significance in validating, detecting and classifying facial features (Karamizadeh et al. 2014; Travieso-González et al. 2021; Valsan et al. 2021; Zhongwei et al. 2021). Moreover, it was used to detect diver's psychophysiological state by classifying EEG (Ahmadi et al. 2021) and sEMG (Lu et al. 2021). The Bayesian extension of the SVM is called Relevance Vector Machine (RVM) and it is used to classify facial features. Compared to SVM, RVM requires fewer training cases (Wei et al. 2021).

Convolutional Neural Network (CNN) is an Artificial Neural Network (ANN) consisting of multiple layers in which each layer has its unique functionality (Albawi et al. 2017; Minhas et al. 2019). CNN has proven efficiency in image data and video recognition, i.e. efficient in detecting facial features (Boucetta et al. 2021; Chen et al. 2021; Christy et al. 2021; Guennec et al. 2016; Xiaofeng Li et al. 2021; Rathi et al. 2021; Ryan et al. 2021; Victoria and Mary 2021; Wang and Qu 2021; Xue-Da SHANG 2021; Zhao et al. 2021; Zhuang and Qi 2021). CNN has a proven ability to classify EEG signals with a good accuracy (Wang et al. 2020). Moreover, HGSR, FGSR and HR were also classified with CNN (Lee et al. 2021).

K-nearest neighbors (KNN) is another supervised machine learning algorithm that measures the distance between the test and the neighboring training samples and subsequently classifies the test sample based on the majority K-nearest training samples. (Wei et al. 2018; Zhang et al. 2017). KNN is used to classify the drivers' psychophysiological state using facial features such as the eyes and mouth (Rathi et al. 2021), and it is also used to classify the sEMG signals (Lu et al. 2021).

Logistic Regression (LR) is considered one of the simplest machine learning algorithms that determine the best boundary between the data (Bamidele et al. 2019). It is used to classify drivers' states using respiration and heartbeat signals (Dong et al. 2021) in addition to sEMG (Lu et al. 2021).

Recurrent Neural Network (RNN) is an artificial neural network that has a temporal storage feature and recursion between the neurons' hidden layers (Li et al. 2019). RNN is used to detect facial features of the eye (Quddus et al. 2021). In conclusion, SVM and CNN look promising machine learning methods that cover wider range of measures in which it can be applied to classify drivers' psychophysiological state as shown in Table 1.

Table 1. Application of machine learning methods with detection measures

	EEG	**EMG/ sEMG**	**Facial features (eye)**	**Facial features (eye and mouth)**	**Respiration and heartbeat signals**	**HBR, FGSR and HGSR**
SVM	✓ (Ahmadi et al. 2021)	✓ (Lu et al. 2021)	✓ (Travieso-González et al. 2021)	✓ (Valsan A et al. 2021; Zhongwei et al. 2021)		
CNN	✓ (Wang et al. 2020)		✓ (Boucetta et al. 2021; Ryan et al. 2021)	✓ (Christy et al. 2021; Li et al. 2021; Rathi et al. 2021; Y. Wang and Qu 2021; Zhuang and Qi 2021)		✓ (Lee at al. 2021)
RNN			✓ (Quddus et al. 2021)			
KNN		✓ (Lu et al. 2021)		✓ (Rathi et al. 2021)		
LR		✓ (Lu et al. 2021)			✓ (Dong et al. 2021)	
RVM				✓ (Wei et al. 2021)		

5. Conclusion

In this paper, we reviewed 30 articles related to the measures that are used to detect drivers' psychophysiological state. Those measures detected fatigue, drowsiness, stress, and distraction. Eight psychophysiological detecting measures were noticed. Each of the measures under discussion has different pros and cons comparatively. It was observed that the most commonly applied measures were the eyes and mouth state measures to deduce the drivers' psychophysiological state. Some of the experiments conducted both real-time and offline applications, but the real-time applications were mostly used by the measures in question.

According to the findings, some of the measures such as ECG, IR trackers, millimeter radar, sEMG can be used online in real-time due to their technological features. On the other hand, regardless of the accuracy and accurate results that other measures such as EEG for assessing drivers’ psychophysiological state, it can’t or needs special technological infrastructure to be implemented in real-time. However, it can be considered as a comparison standard for real-time studies. Finally, several machine learning methods had been observed applicable on different detection measures. SVM and CNN had a wider range of classifying drivers' psychophysiological measures.

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Biographies

Shaima Alameeri is currently a master's student at University of Sharjah, College of Industrial Engineering and Engineering Management. In 2018, she obtained her Bachelor's degree in Electrical and Electronics Engineering at University of Sharjah, UAE.

Imad Alsyouf is a professor of Industrial Engineering at the Industrial Engineering and Engineering Management Department at University of Sharjah, UAE. He is Director of the University Sustainability Office, in addition, he is the founder and Coordinator of Sustainable Engineering Asset Management (SEAM) Research Group, Research Institute of Science and Engineering (RISE) at the same university. He has more than 97 conference and journal papers published. His research interest includes sustainability, reliability, quality and maintenance engineering, Total Quality Management (TQM), Lean Production, productivity improvement, performance measurement, life cycle cost analysis, Innovation Management, and optimization.

Ahmad Alzghoul is a lecturer at the department of Data Science at Princess Sumaya University for Technology in Jordan. He has obtained his bachelor's degree in Computer Engineering in 2005 from Mutah University, Jordan. Then he completed his Master's degree in Computer Engineering, specialized in intelligent systems at Halmstad University (Sweden), moreover he received a Master's degree in Software Technology from Linnaeus University (Sweden). In 2013 he obtained his PhD in Computer Aided Design within the field of Computer Science and Engineering at Luleå University of Technology, Sweden. He has more than 11 peer-reviewed published journal papers, in addition to 8 conference papers.

Hossam Almahasneh has a PhD in AI and Cognitive Neuroscience. He is the founder of the Intelligent Era. Moreover, entrepreneurs for AI solutions and consultancy. He is a member of Jordanian Association of AI and Entrepreneurship, and a certified AI/ML/BI trainer. He is a Former Digital Transformation Consultant with Dubai Government. He is an adjacent lecturer with many local and international universities. Moreover, he is a researcher in AI field with many local and international organizations. He achieved many patents in AI/ cognitive Intelligence and neuroinformatics. Finally, he is an affiliated research member with the University of Sharjah.

Omar Jaradat is a senior safety expert at Qamcom Research and Technology in Sweden. He has a PhD in Safety-Critical System Engineering from Mälardalen Univerity, Sweden. Omar's main experience and research interest are safety assurance for embedded systems, developing and establishing change management processes for safety systems, the implications of machine learning role in safety assurance, and Advanced Driver Assistance Systems (ADAS) as well as Autonomous Driving (AD) systems design and safety assurance. Omar has 18 published scientific articles within the scope of safety-critical systems engineering.

Abdul Kadir Hamid he is a professor at the Electrical Engineering Department at the University of Sharjah, UAE with 22 years of experience at this university. He obtained his bachelor's degree in Electrical Engineering in 1985 from West Virginia University & Institute of Tech., Montgomery, West Virginia, U.S.A. He studied Electrical Engineering at the University of Manitoba, Winnipeg, Manitoba, Canada and obtained his M.Sc. and PhD degrees. He has more than 91 published journal articles, in addition to over 108 conference papers.

Anwar Jarndal is an associate professor at the Electrical Engineering Department at the University of Sharjah. He obtained his B.Sc. degree (with honors) in Electronics and Communication Engineering from Applied Sciences University, Amman, Jordan, 1998. Then he obtained his M.S. degree in Electronic and Communication Engineering from Jordan University of Science and Technology, Irbid, Jordan, 2001. He studied Electrical Engineering from the University of Kassel, Germany and obtained his PhD degree in 2006. In 2008, he completed his Post-doctoral fellow at Ecole de Technologie Superieure of Quebec University, Montreal, Canada. He received more than 7 awards and honors. He taught several courses such as Electric Circuits Analysis, Fundamentals of Electronics, Electronic Circuits, Digital Electronics, Digital Design, Microelectronics, Analog Communications, Digital Communications, Communication Systems, Wireless Communications, Computer Networks, Control Systems, C programming, Matlab Programming, etc. He has more than 41 published journal articles, in addition to over 53 conference papers.