

# Developing a Smart IoT based Traffic Management System

## تطوير نظام ذكي لإدارة السير وتنظيم المرور استناداً إلى إنترنت الأشياء

**Yousef W. Sabbah**

Assistant Professor/ Al-Quds Open University/ Palestine  
ysabbah@qou.edu

**يوسف وجيه صباح**

أستاذ مساعد/ جامعة القدس المفتوحة/ فلسطين

**Mohammad Shafeeq Abu Qare'**

Al Bader Technologies Co./ Palestine  
mohammad.abuqare@gmail.com

**محمد شفيق أبو قرع**

شركة البدر للتكنولوجيا/ فلسطين

**Nizar Salim Barakat**

Ministry of Transportation/ Palestine  
nizar.mot@gmail.com

**نزار سليم بركات**

وزارة النقل والمواصلات/ فلسطين

**Jameel Shhadi Sayed**

General Administration of Palestinian Police/ Palestine  
jsayd18@gmail.com

**جميل شحادة سيد**

الإدارة العامة للشرطة الفلسطينية/ فلسطين

**Mohammad Fawaz Najwan Salmiyeh**

BCI (Bnet) Co./ Palestine  
mabunajwan@gmail.com

**محمد فواز نجوان سالمية**

شركة BCI (Bnet) / فلسطين

**Yousef Dawood Salameh**

The National Bank/ Palestine  
yousef405555@gmail.com

**يوسف داود سلامة**

البنك الوطني / فلسطين

**Salah Rayyad Baddwan**

Ahbab Rahman Model School/ Palestine  
salahrayyad@gmail.com

**صلاح رياض بدوان**

مدرسة أحباب الرحمن النموذجية/ فلسطين

**Ahmad Mhmouad Al-Najjar**

Technology Investment Co./ Palestine  
aalnajjar399@gmail.com

**أحمد محمود النجار**

الشركة التكنولوجية للاستثمار/ فلسطين

**Ihab Salah Hamdan**

Ministry of Higher Education/ Palestine  
ihab.hamdan@gmail.com

**إيهاب صلاح حمدان**

وزارة التعليم العالي/ فلسطين

Received: 24/12/2020, Accepted: 28/03/2021

DOI: 10.33977/2106-000-004-007

http://journals.qou.edu/index.php/PJTAS

تاريخ الاستلام: 2020/12/24، تاريخ القبول: 2021/03/28

E-ISSN: 2521-411X

P-ISSN: 2520-7431

## ABSTRACT

This research paper emerged from the urgent need to address traffic offenses and the accompanying accidents and reduce traffic congestion by developing a smart traffic management system (STMS). The proposed system serves the competent authorities (e.g., the traffic department and the traffic police) in traffic control to reduce traffic offenses and accidents and preserve properties and lives. As such, the system will target drivers, regardless of the type of vehicle they drive. The system handles three major offenses: Running a red light, over-speeding, and parking in a prohibited space. The system consists of two main parts, a hardware that consists of controllers and sensors to track offenses as soon as they occur and a web application that records these offenses. It comprises the hardware and software components to issue e-tickets to be sent to offenders in short messages specifying the time, type, and fine of each offense ticket to prevent them from recommitting offenses. It also provides a congestion control model at traffic signals on road junctions. In the system analysis phase, data collection was conducted using two instruments, a questionnaire as a quantitative instrument, which was analyzed using the statistical package for the social sciences (SPSS), and personal interviews as a qualitative instrument, which was analyzed through thematic coding and content analysis to classify themes and subthemes. In the development phase, a prototype was developed and tested for running the red light offenses, and the results were generalized to the other types of offenses because they are built on the same basis. The obstacles and challenges were identified, and recommendations were set on the ways to overcome these offenses by involving the targeted drivers and the community in the development process to raise awareness in this regard. In addition, the proposed system can serve the community by providing a transparent system, and at the same time, increasing the government

income and reducing the risk of traffic accidents resulting from offenses.

**Keywords:** Fines, IoT, Issuing e-Tickets, Over-speeding, Running a Red Light, Smart City, Track and Detect Offenses, Traffic Accident, Traffic Management System, Traffic Offense.

## المخلص

تنبع فكرة المشروع البحثي من الحاجة الماسة إلى معالجة مشكلة مخالفات السير، وضبط أنظمة المرور، وتقليل الازدحامات الخانقة. إذ يسهم النظام الجاهز المختصة ويخدمها (دائرة السير وشرطة المرور) في ضبط نظام المرور والحد من المخالفات، وبالتالي تقليل الحوادث المرورية والحفاظ على الممتلكات والأرواح. وبذلك فهو يستهدف فئة السائقين بغض النظر عن نوع المركبات التي يقودونها. يعالج النظام ثلاث مخالفات رئيسية هي تجاوز الإشارة الحمراء، وتجاوز السرعة، والاصطفاف الممنوع. يتكون النظام من جزأين أساسيين، المعدات الإلكترونية من مجسات ومستشعرات ومتحكمات لرصد المخالفات فور حدوثها، ونظام محوسب وقاعدة بيانات تسجل هذه المخالفات. فهو يجمع بين المكونات المادية والبرمجية لتمكنه من إصدار مخالفات إلكترونية فورية لمركبتها، تصلهم عبر رسالة قصيرة تحدد وقت المخالفة وطبيعتها وغرامتها، لمنعهم من ارتكابها مرة أخرى. كما يوفر نموذجاً لمراقبة الازدحام المروري، والتحكم بزم من إشارات المرور على مفترقات الطرق. تم العمل على جمع البيانات وتحليلها من خلال أداتين، الاستبانة كأداة كمية، وقد تم تحليلها باستخدام حزمة التحليل الإحصائي (SPSS)، كما تم تدعيمها بالمقابلة الشخصية كأداة نوعية، وتم تحليلها باستخدام الترميز وتحليل المحتوى، وإعداد المحاور وتصنيف النتائج. كما تم إعداد النموذج الأولي (Prototype) للجزء الأول من النظام الخاص بتجاوز الإشارة الحمراء، وتم اختباره وتعميم النتائج على بقية المخالفات كونها بنيت على الأساس ذاته. وتلخصت طرق الاستفادة من نتائج البحث في تعميمها ونشرها، يضاف إلى ذلك تحديد المعوقات والتحديات، والتوصيات المتعلقة بسبل التغلب عليها، وإشراك الفئة المستهدفة من السائقين وأفراد المجتمع في عملية التطوير، وزيادة الوعي بهذا الشأن، وخدمة الحكومة

والمجتمع بتوفير نظام شفاف يزيد من دخل الحكومة، ويقلل مخاطر الحوادث المرورية الناجمة عن المخالفات.

الكلمات المفتاحية: إنترنت الأشياء، إصدار مخالفات إلكترونية، تجاوز الإشارة الحمراء، تجاوز السرعة، حوادث السير، غرامة، كشف المخالفة ورصدها، مخالفة السير، المدن الذكية، نظام إدارة المرور.

## INTRODUCTION

Recently, in light of the remarkably vast spread of the number of vehicles in Palestine and the inadequate infrastructure in the Palestinian cities, the number of traffic accidents has increased steadily, causing a significant loss in lives, public and private properties (Ministry of Transportation, 2020). Prior to delving deep into the research topic, it is essential to identify and define the most important concepts in the context of STMS. Traffic signs direct the flow of traffic and display the rules of the road. Warning signs are triangle-shaped signs that show changes in the road's structure, whereas guide signs are round-shaped signs that regulate the traffic movement and clarify where and when vehicle crossing is allowed. The signs' height is 1.5-2.5m and is placed 1-4m away from the edge of the road, such as the stop and slow signs. In addition, road markings are effective tools to regulate traffic movement in streets; usually, they are used to improve the effectiveness of traffic signs and guide the drivers to road instructions directly. Traffic signals/lights are used to regulate the movement of all types of vehicles. By altering the color of the light, drivers and pedestrians know when to stop and when to renew the movement (Abu Ahmed, 2003).

Internet of Things (IoT) is a network of devices interacting with each other, where they can sense, capture and transfer data over the Internet without any human intervention. Humans have limited time, attention, and accuracy in capturing data of things in the real world. With the help of computers and the Internet, they will be able to gather sufficient data that enables them to track and count everything reducing time and cost. IoT is based on four stages: actuators and sensors, data acquisition, pre-processing (edge analytics), and cloud analytics. IoT platforms can be used to collect data within a wide geographic area with remote monitoring and control tools and process them for early warning. Therefore, IoT applications can be used in several fields, such as

smart cars, homes, transportation, healthcare, etc., to constitute smart cities (Bharani, 2020).

This paper was set out to find suitable solutions by employing smart cities, mainly the Internet of Things (IoT) in the transportation domain. The proposed solution assists the traffic department and the traffic police to manage, prevent and detect traffic offenses. This research aims to design and build a Smart Traffic Management System (STMS) that integrates hardware components such as cameras and sensors to capture related data. The detected offenses are recorded on a central database on the cloud, and their e-tickets are issued and sent to the offenders using an SMS server. Accordingly, the essential national benefit of the proposed STMS stems from setting out precautions that minimize the risks and reduce damages of public and private properties and loss of people's lives due to traffic accidents resulted from offenses, as the first stage of Palestinian smart cities. It automatically detects different types of offenses and issues e-tickets accurately. Sustainability is granted through traffic offense fines, especially compensation from undetected offenses due to the lack of human resources or the circumvention of drivers from paying the fines.

This research is limited to three traffic offenses, including running a red light, over-speeding and parking in prohibited public places. The developed prototype was applied to a sample of both vehicles and traffic lights that were tested for a specific period while keeping records of the readings and results. The study population included drivers of public transportation in Ramallah and al-Bireh district, where a sample was selected to complete the data collection instruments, entailed conducting a survey on their opinions using questionnaires and interviews. The data were analyzed using the appropriate qualitative and quantitative data analysis tools based on thematic coding and SPSS, respectively. In contrast, another method was based on developing a prototype to be applied, operated, and tested in some selected locations, paving the way for building a comprehensive and broader system in future studies if sufficient funding can be allocated.

The paper consists of six sections, starting with this introduction as the first section. The second section presents a literature review. The

problem statement is covered in the third section, and the proposed STMS is depicted in the fourth section. Finally, the fifth section provides the research results and discussion, and the sixth section provides the conclusion and the recommendations.

## LITERATURE REREVIEW

As part of the global smart-city agenda, digital technologies became the backbone of smart cities to enhance urban infrastructure quality. This approach will enable our cities to be efficient, green, and technologically advanced. Moreover, sustainability development has a significant impact on planning smart cities to create sustainable smart cities. In this context, we focus on enhancing the environment to reduce pollution from different resources. Therefore, attention to the combination of technology and the environment is the most efficient way to constitute the 21st century's ideal cities. The smart city transport concept is considered a future vision aiming to investigate the urban planning process and construct policy-pathways to achieve future goals. In addition, this trend will address the severe global challenges related to ecology, society, economy, and good governance (Yigitcanlar, Han & Kamruzzaman, 2020).

One of the most important issues related to the Intelligent Transportation System (ITS) and smart cities is the Traffic Management System (TMS). The ITS collects traffic-related data that enable travelers to select traveling modes and paths and departure times. With the growth of the number of vehicles recently, traffic congestions increased; thus, the number of traffic offenses increased. Information technology can provide solutions to several traffic and transportation issues, and the IoT assists in traffic-related data collection (Varun Chand & Karthikeyan, 2018).

In the motion towards smart traffic management systems, Singh, Alok, Manav, & Kandari (2019) implemented a density-based traffic controller with defaulter identification using IoT. It constitutes an offender detection module that identifies the vehicles that runs a traffic signal when the light is red. An IR sensor detects the presence of an offender at the junction and triggers a camera to take a snapshot of the plate number of the offender's vehicle using the AMCap application. The plate's image is sent to

the monitoring device and is displayed on a special webpage with the incident's relevant information of the offense. In order to minimize road accidents due to over-speeding, Jeddi, Hassouna, Shahin, & Mir (2016) proposed a monitoring and transmitting device embedded in every vehicle that monitors over-speed offenses continually and sends relevant information to a central database, which in turn compares the actual speed of the vehicle with the defined speed limit of that road, and identifies offenses accordingly. A prototype device was successfully implemented and installed in a vehicle for testing and evaluation purposes. This device consists of GPS/GSM908 module, antenna, SIM card, Atmel 32 bit microcontroller, impact detector, SD card, and power supply. It records the position, time, and date from a GPS satellite in real-time, where the vehicle's speed, position and ID are transmitted to the central databased every 10s.

For vehicle identification, which is essential in TMS, some researchers used cameras and image processing of vehicle plates to extract its ID using OCR (Singh et al., 2019). Others used a vehicle-embedded device that stores the vehicle's ID with a transmitter that transmits it to a central database (Jeddi et al., 2016). But QR code could be an innovative solution, where the vehicle's ID can be inserted in a QR code that appears on the plate, then a QR reader will perform very well with high accuracy (Jichkar, Deulkar, Thakare, Bolakhe, & Vaidya, 2019). Moreover, Radio Frequency Identification (RFID), which are small electronic devices that consist of small chips and antennas, can be used for automatic vehicle identification using electromagnetic fields (Angeline, Aswini, Devadharshini, Gousalya, & Aravind, 2018). This technique can be used by traffic monitoring systems or police to identify the vehicle using an RFID reader that provides all information related to that vehicle, including previous offenses, owner's information, and if the vehicle has pending offense cases with unpaid fines. In addition, an invention was registered by (Palmer & Aharoni, 2013) in the USA for collision prediction and traffic violation detection. It refers to a system for monitoring, analyzing, and reporting traffic offenses at a predetermined area in real-time, prospectively, or retrospectively.

Yogheshwaran, Praveenkumar, Pravin, Manikandan, and Saravanan (2020) proposed an

IoT-based intelligent traffic control system that deals with emergency cases when an Ambulance is delayed due to traffic that puts saving our life in jeopardy. In their model, they considered that over-speeding is the main issue prevailing offenses and is difficult to control. In order to overcome this issue, it is necessary to force vehicle drivers to slow down and stop in probable accident areas. They developed a model that controls the speed of the vehicles forcing drivers to stop at red signals. Furthermore, Javaid, Sufian, Pervaiz, and Tanveer (2018) proposed a hybrid IoT-based STMS with an algorithm that optimizes traffic flow efficiently and manages traffic signals using an input of traffic density from cameras and sensors. They used RFID to prioritize the emergency vehicles (e.g., ambulances and fire brigade vehicles) during a traffic jam. In order to measure the effectiveness of the proposed system, they developed a prototype that is connected to a centralized database and presented the important data in a graphical format to assist the authorities in developing future road plans. On the same concept, Sharif, Li, Khalil, Kumar, Sharif, and Sharif (2018) proposed a low-cost STS to provide a better quality of service for public traffic management. They fixed low-cost sensors every 500 meters to obtain updated traffic data for further real-time processing to analyze traffic density and predict scenarios to solve traffic issues.

In order to overcome the disadvantages of traditional traffic management techniques, Das, Dash, and Mishra (2018) developed an RFID-based model that reduces installation time and maintenance cost and monitors the motion of tagged vehicles. Similarly, Rath (2018) suggested an enhanced traffic control and monitoring framework that transmits quick information with their corresponding actions using Vehicular Ad-hoc Network (VANET) with a mobile agent-based controller that depends on a congestion control algorithm to regulate the traffic flow. He carried out his experiments using NS2 simulation and obtained acceptable results with reduced delays and accidents. Moreover, Janahan, Veeramanickam, Arun, Narayanan, Anandan, and Javed (2018) proposed another model for traffic signal monitoring using vehicle counts. It optimizes the timing interval of the traffic signal based on the number of vehicles on a particular

roadside. It can decrease the waiting time for the drivers to crossroad signal, using a clustering model based on K-Nearest Neighbors (KNN) supervised learning algorithm. They implemented the model on a traffic network and real-time traffic sub-networks to measure the effectiveness. The results are displayed for the Admin to monitor traffic flow using multiple IR sensors, and clients can check the traffic flow anytime.

Many researchers follow similar smart IoT-based TMSs that control traffic congestion, especially at road crossings. IoT based intelligent traffic congestion control system for road crossings (Sadhukhan and Gazi, 2018), IoT based intelligent transportation system (IoT-ITS) for global perspective (Muthuramalingam, Bharathi, Kumar, N. Gayathri, Sathiyaraj and Balamurugan, 2018), and IoT based street lighting and traffic management system (Saifuzzaman, Moon and Nur, 2017).

A group of scientists at Carnegie University developed a smart traffic signal system, which was tested in Porto city. It was installed in about 450 taxis; this new system will replace the traditional traffic lights with virtual ones that appear on the windshield or the dashboard of the vehicle. Each driver will get relevant information showing how long he/she will wait at a traffic light (Abdulmunem, 2015).

An STMS has been applied in China to help the police deal with traffic offenses and accidents quickly and reduce traffic jams, which was named “City Brain.” (Abigail Beall, 2018; Yi, 2017). This system detects traffic accidents within one second, which enables the police to reach the accident site within five minutes from receiving a warning. This system has achieved remarkable results in one year since its operation. The system controls traffic lights in 128 intersections, of which 100 intersections have completely dispensed the human factor. This reduced transportation time by 15.3% and saved 4.6 minutes of transportation time on highways. The system receives more than 500 warning notifications per day in the main regions, with 92% accuracy level.

Saher system regulates traffic in KSA based on a Dutch technology from Gatsometer that consists of a network of digital cameras connected to an information center. It technically verifies traffic offenses, then requests the vehicle owner’s information from the database, and issues tickets

related to speeding and running traffic signals (“Saher System”, 2020; “Inventor of Saher System”, 2015). The Saher system achieved the highest level of traffic safety and improved the performance of traffic staff. Saher disadvantages include obstructing rescue vehicles, such as ambulances, as some drivers deliberately refrain from giving space because of fear of committing other kinds of offenses the system records. In addition, the lack of speed limit signs in some streets causes drivers to make sudden halts when they discover the cameras.

A group of researchers at the Massachusetts Institute of Technology (MIT) developed an advanced, smart system for managing traffic lights to reduce delays, improve efficiency, and reduce emissions produced by vehicles (Husni, 2015). The system collects big data from the roads and vehicles in the surrounding areas analyzed accurately to recognize traffic patterns and produce better information for traffic management. It is based on algorithms that allow the traffic prediction and the flow of vehicles on certain roads and provides the ideal procedures and periods to reduce traffic jams.

In the English city of Milton Keynes, researchers have proposed a smart traffic system in Vivacity Laboratories based on artificial intelligence, which reduces congestion on the roads (“Smart Traffic Lights”, 2017). Smart traffic lights monitor speed and congestion while prioritizing traffic for ambulances with green light, in addition to relying on thermal maps to analyze how pedestrians and vehicle drivers use the roads. The project employs 2,500 sensors to control major road junctions and parking lots. The smart signals are equipped with cameras, which help determine traffic priorities for bicycles, buses, and ambulances with green lights. It is a new technology which enables traffic lights to communicate with self-driving vehicles located nearby and send warning signals while pedestrians cross the streets.

In Germany, the colors of the smart traffic lights do not change in a constant sequence and time; rather, they depend on the traffic congestion (Alkhatib, 2013). On this basis, it can prolong the time-lapse of the green color when it spots an old man who was late in crossing the street or when it detects a child carriage stumbling on the road. These smart lights operate with cameras and

sensors of pressure and temperature and regulate pedestrian traffic according to the flow of vehicles and the number of pedestrians. For example, the system can extend the time of the green color from six to twelve seconds. Lasers and infrared rays are used to regulate traffic, as infrared rays detect the distance between vehicles and predict congestion. Therefore, it directs vehicle drivers through navigation devices or radio to adopt a certain speed. In contrast, laser rays alert the driver to the passage of a child or a bicycle on his/her right side when turning by emitting a warning sound.

The idea of the traffic system in Toronto is based on reducing waiting times and harmonizing traffic lights with the flow of vehicles (Hussein, 2014). The researchers were able to design smart traffic lights using the Marlin-ATSC system that reduces waiting time. It relies on game theory, artificial intelligence algorithms, and sensors. It dynamically adjusts green and red light periods according to the actual flow of traffic, saving money, reducing wasted time and carbon emission.

The Public Works Authority in Qatar announced the start of the first phase of operating an e-system that allows traffic lights to identify civil defense vehicles and ambulances to open for them automatically (Hafez, 2014). The new e-system changes the traffic lights to green when the rescue vehicles approach the selected intersection/junction with traffic signals and helps the vehicles reach the scene of the accident quickly and safely. The system consists of three main components, a vehicle-mounted control unit, a receiver unit installed at the intersections, and a central management system. Two researchers at al-Quds Open University developed a similar system for controlling traffic lights in emergencies through emergency vehicles via mobile phones (“Entrepreneur Stories”, 2014). A device that controls the traffic lights was developed by a control message sent by the emergency vehicle driver to a specific mobile number that identifies the traffic light via a GSM module fixed on it. In emergencies, the ordinary traffic system is replaced with the emergency system until the emergency is finished.

In the Palestinian context, the Judge and chairperson of the Ramallah Court of First Instance stated that the weekly average of traffic cases in Ramallah is about 1,000 offenses per

session, that is, an average of 8000 traffic offenses per month since the court holds eight sessions per month. The Judge clarified that there is a huge number of traffic offenses, and the process of tracking them takes a lot of effort from the court and the related authorities in terms of detection, retrieval, recording judgments, organizing judgment summaries, and transferring them to the Public Prosecution, in order to be executed by the police (Shasha News, 2014).

The previous studies show that most of the previous TMSs focus on traffic flow management and congestion control, while none mentioned traffic offense detection, which is the major reason for traffic congestion and accidents. This paper sets out a radical change in transport and traffic management systems in Palestine. In addition to traffic monitoring and control, our proposed STMS deals with traffic offenses that include prevention, detection, recording, ticket issuance, and execution.

## **PROBLEM STATEMENT**

The research problem lies in the risks and losses resulting from traffic congestion and the consequent offenses committed by drivers of different vehicles, which the traditional traffic management system cannot detect; in case there were no traffic police present at the corresponding moment. The shortcomings of the traditional system to detect traffic offenses cause accidents and losses in lives, public and private properties. This situation increases the financial burden on the state treasury in treating the injured and repairing the resulting property damages or losses, in addition to losing the ticket fees of the undiscovered offenses. Moreover, results of the qualitative and quantitative instruments of this research emphasize the importance of developing our proposed system, where the participants insisted that the Palestinian cities need to develop an STMS that uses cameras, sensors, and radars, to ensure the application and transparency of the traffic law, referring that traffic offenses are the major reason for traffic accidents. However, this requires suitable infrastructure and a sufficient allocated budget. They also suggested that the STMS should be able to inform the vehicle owners of any offenses that occurred while driving their vehicles by the others in order to take the needed precautions. Finally, they called to evaluate the

relevance of the offense fines to the nature of the offenses and applying suitable penalties. In its annual statistical report, the Ministry of Transportation (2020) reported that the traffic police issued 231363 traffic offenses in 2019, with an increase of 10079 above 2018, 25% of which in Nablus district, 21% in Ramallah, and 18% in Hebron. Moreover, the number of traffic accidents due to traffic offenses reached 13165 accidents, causing 10846 injuries and 126 death. Most of these accidents occurred in Ramallah with 27% and Nablus with 20%. Therefore, the proposed STMS comes to address the described issues related to traffic congestion and offenses that would cause material damage and heavy losses amounting to the losses of human lives or that may cause permanent or temporary disabilities.

## **DESIGN AND IMPLEMENTATION OF THE STMS**

The researcher developed a prototype for the proposed STMS following the system development lifecycle in four phases: analysis, design, implementation, and testing. The system analysis was based on a survey that consists of a personal interview and a questionnaire for a sample of the target audience, which focused on the vehicle drivers.

### **System Analysis and Requirements**

The system's requirements and needs assessment were based on a survey, which shows the lack of a smart traffic system and unjust application of the traffic laws. In addition, police presence on the roads on a regular basis contributes to reducing traffic offenses, but drivers change routes to bypass the police. Moreover, results reveal the lack of sufficient awareness among the relevant authorities on traffic laws and systems, the penalties imposed on the drivers are not deterrent, and they tend to deny offenses by providing false excuses. Finally, traffic offenses are the major cause of traffic accidents and congestion, and the current traffic system is not so efficient to deal with these issues. Therefore, a traffic management solution is needed to reduce traffic offenses and accidents, prevent using illegal vehicles and issue penalties for traffic offenders by implementing an advanced TMS that uses cameras to detect traffic offenses automatically. This will promote transparency and integrity by enacting laws related to pleas in courts since drivers

disagreed on the relevance of the fines to the nature of the offenses. They suggested re-evaluating the relevance of the offense fines and applying stricter penalties. They emphasized developing a smarter system that uses cameras, sensors, and radars for auto-detection of traffic offenses. Moreover, results, which will be elaborated in subsection 5.2, yield that 95% of the offense penalties were based on fines, and 24% of the drivers were totally unconvinced that they deserved the traffic offenses issued in 2019. Moreover, 32% of the drivers caused 1-2 traffic accidents, where 68% of these accidents (68%) were due to traffic offenses, causing physical and material damages, as well as losses in people's lives and public properties. The number of traffic offenses steadily increased among drivers who usually drive for more than three hours per day, mainly due to fatigue or zoning out. In addition, there was a significant relationship between the number of traffic tickets and accidents. Therefore, the proposed solution should overcome the mentioned issues to support the traffic authorities to control traffic offenses.

### The STMS Design

Figure 1 shows the block diagram of the proposed STMS, where a central processing unit controls all operations, receives data from the sensors and cameras, analyzes it, and issues the appropriate commands when a traffic offense occurs. The system consists of three main units; the Traffic Management and Congestion Control Unit (TMCCU) is the central unit responsible for system management and decision making when a traffic offense is detected. It receives offense information from a Traffic Monitoring Unit (TMU) related to the detected traffic states and offenses. When a driver commits a traffic offense, the Vehicle Identification Unit (VIDU) identifies the vehicle's ID using image processing or extracts it from the vehicle's memory. It can identify its driver's ID through a query to the Traffic Offense Recording Unit (TORU), which in turn records the offense, issue an e-ticket, and sends it to the driver's phone using a messaging server.

The TMU consists of cameras and sensor modules, as shown in Figure 2. The traffic sensor module is connected to the Raspberry Pi main processing unit via an Arduino controller. It monitors the roads and junctions where a sensor control triggers the relevant sensor on some events to collect data from the laser, speed, or magnetic

sensor. The TORU block chart is depicted in Figure 3. It connects the main processing unit to the centralized police database and the messaging server, when necessary, via a secure link to the Internet through a connection module (e.g., Ethernet or 3G/4G). It responds to queries regarding vehicles and drivers, records offenses, issues e-tickets, and sends them to the drivers. Figure 4 illustrates the VIDU, which is based on RFID technology and positioned between the TMCCU and the TMU. In addition, the vehicle's ID controller consists of NRF 2.4GHz, RF 433MHz, and RFID modules. It connects the road/vehicle sensors to the main processing unit. Different RF modules are used for different distances between communicating devices; for example, we need to connect all Arduinos to all traffic lights at a junction for synchronization issues. Moreover, the RF433MHz is used for a short distance to prevent interference between different transmitters of vehicles and the receiver of each lane. In addition, nRF2.4 can be used for over-speeding offenses as described below. As shown in Figure 5, the TMU is responsible for traffic offense detection. It is connected to the Raspberry Pi processing unit that enables both camera and laser sensor modules. These modules collect data related to traffic offenses. The TMU is integrated with the VIDU that recognizes offending vehicles either via pairing with the vehicle's transmitter or via character recognition of the vehicle's plate number.

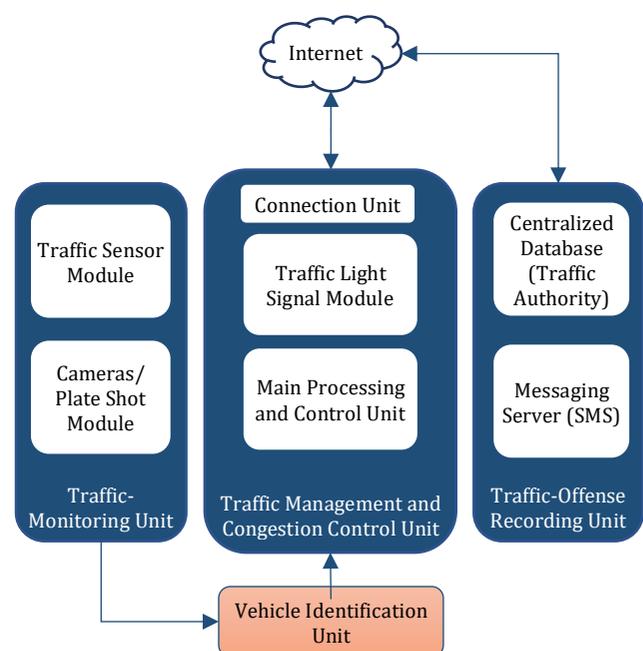


Figure 1 Block Diagram of the Proposed STMS

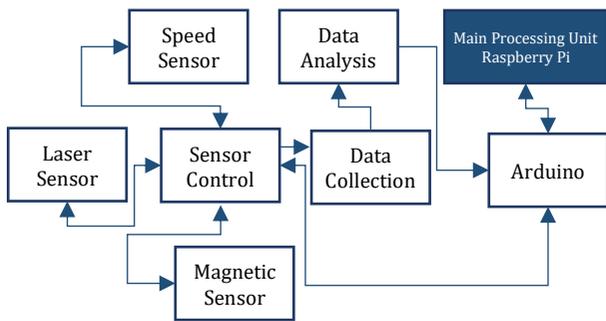


Figure 2 Traffic-Sensor Module

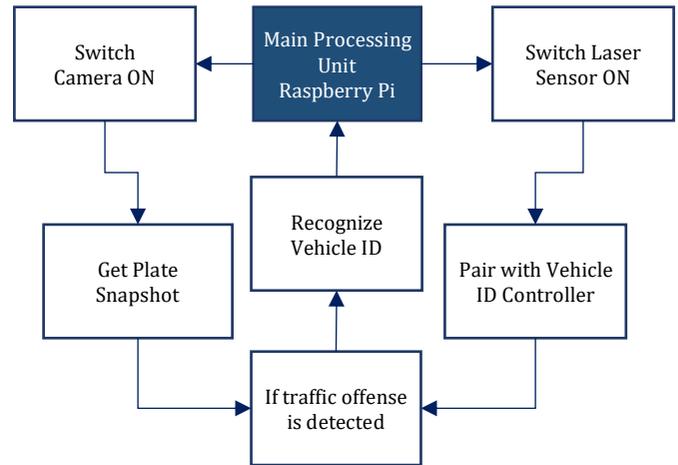


Figure 5 Traffic Monitoring Unit (Traffic-Offense Detection)

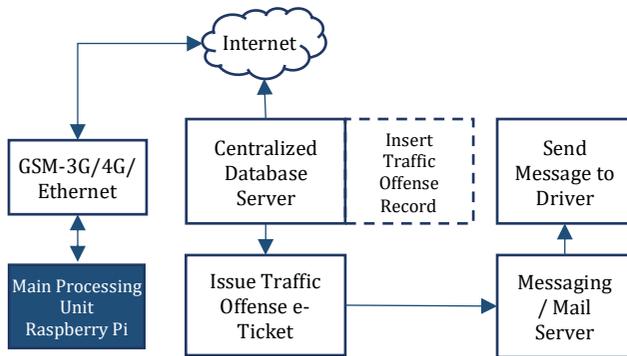


Figure 3 Traffic-Offense Recording Unit

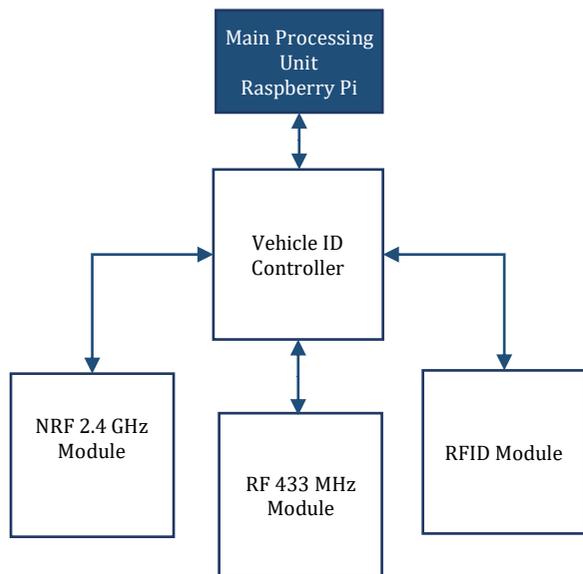


Figure 4 Vehicle ID Unit (RF Module)

For the over-speeding offense, a vehicle speed sensor and a GPRS are embedded on the vehicle to detect its speed compared with the speed limit of that location. When it exceeds the speed limit, a query is sent to the database to identify its owner /driver, and the system issues an e-ticket indicating the speed limit, the speed of the vehicle, and the vehicle’s information; it then sends a notification to the driver and the competent authorities. However, for privacy concerns, an inexpensive alternative solution can be based on nRF2.4, where a transmitter in the vehicle connects to the nearest receiver installed on the road (e.g., every 2km), maintaining the coordinates of each receiver on the central database. The speed limit can be obtained from a memory attached to each receiver. For prohibited parking, the STMS employs a QR code reader embedded in the vehicle that extracts information from a QR code on the prohibited parking sidewalk and operates in the same procedure above. The e-ticket indicates the location and description of the offense, such as a red-white sidewalk or a pedestrian crossing.

The centralized police database of the proposed STMS consists of six entities with vehicle ID as the primary key. The first entity identifies the vehicles with three attributes (license number, brand and description). Another entity identifies the geographical distribution of the Arduino controllers and their status (e.g., whether they are functioning or not) with four attributes (vehicle license number, driver ID, Arduino ID, and status). The third identifies the driver through (driver name, ID, driving license type, effective

and expiry dates, mobile number, and e-mail). The fourth entity identifies traffic offenses to be recorded when they occur with eight attributes (driver and vehicle IDs, offense number, date and time, fine payment due, and initial/final amounts, as well as notes). Finally, two more entities identify vehicle license type and traffic offense type.

## EXPERIMENT SETUP

Figure 6 shows a block diagram of the prototype of our proposed STMS related to running red signals, which provides a testing and experiment setup. When the traffic light becomes red, the sensors or cameras turn on and recognize the ID (e.g., the plate number) of the vehicle committing a traffic offense. The researcher used image processing openALPR<sup>1</sup> open-source library to recognize the plate number. In turn, the system sends a query via a secure communication link through the Internet to a central database of the traffic police, inquiring the mobile phone number

of the owner and/or the driver of the vehicle. Then, the system records a traffic offense, issues an e-ticket, and sends it immediately to the offender's mobile phone, specifying the offense location, time, and fine amount. The same procedure is applied to other traffic offenses with some modifications depending on the offense type and requirements. The prototype consists of four modules:

1. The vehicle's transmitter (e.g., TX RF 433MHz) that contains its ID (i.e., plate number).
2. The road's receiver (e.g. RX RF 433MHz), which is fixed on the junctions.
3. The internet connection module, which connects to the central database via an Ethernet or GSM 3G/4G shields.
4. The main processing unit using Raspberry Pi with a Pi Camera.

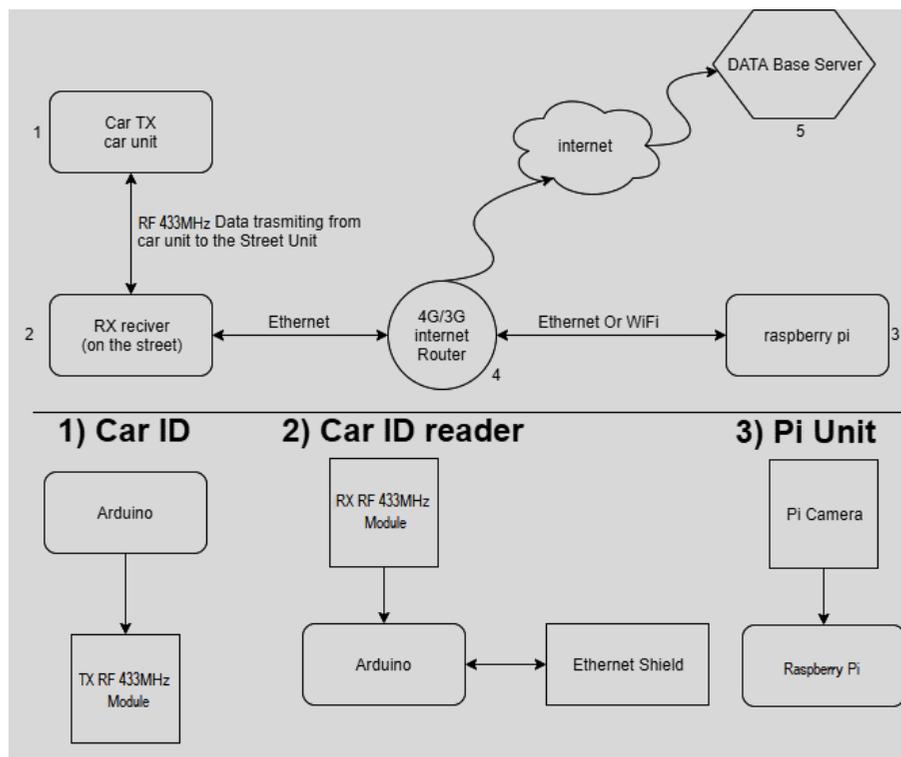


Figure 6 The Case of Running Red Light Offense Detection using Pi Camera.

When the traffic signal is red, and the vehicle passes over the RX RF 433 MHz receiver module installed underground on each lane and connected

to the Arduino, the TX RF 433MHz transmitter installed inside the vehicle sends the vehicle's ID to the receiver. Then, the Arduino creates a TCP connection with the Raspberry Pi through the

<sup>1</sup> GitHub. Retrieved 2012, February 21 from <https://github.com/openalpr/openalpr.git>

Internet connection module and sends the information to it, so the Raspberry Pi turns on the camera and captures the image of the offending vehicle. Accordingly, the Raspberry Pi creates another connection to the database server through a VPN connection to store the traffic offense data, including a timestamp, the vehicle’s ID, and image while crossing the red signal and the offense penalty. The server issues an e-ticket, executes a query to extract the driver’s phone number and sends the e-ticket to him in a text message via an SMS server.

## RESULTS AND DISCUSSION

This section shows the system testing results through practical experiments on the prototype for the case of running a red light. In addition, it covers the results of the survey based on the quantitative instrument (e.g., the questionnaire). It also provides an in-depth discussion of the results.

### THE STMS TESTING RESULTS

In order to prove the concept and to test the proposed STMS, the researcher conducted two experiments on the prototype since it was prohibited to fix it on a real traffic light, and the production of a real system requires more funds and sophisticated hardware and software. At a fixed speed of 70km/hour, we measured the response time and distance, the number of recorded traffic offenses (i.e., issued tickets), the number of received tickets through messages, and the offense-detection accuracy for a sample of 100 trials. The experiments were repeated five times at different timings (Morning, Afternoon, Evening, Night, and Late Night) and weather conditions (e.g., Sunny and Rainy). The results are averaged and summarized in Tables 1 and 2.

Table 1. Results of the Experiment in Sunny Weather

Timing	Avg. Response Time (s)	Avg. Response Distance (m)	Speed (Km/Hr.)	Recorded Traffic Offenses	No. of Received Messages	Offense-Detection Accuracy (%)
Morning	0.50	09.7	70	95	92	95
Afternoon	0.45	08.8	70	93	85	93
Evening	0.50	09.7	70	89	80	89
Night	0.58	11.3	70	78	75	78
Late Night	0.56	10.9	70	75	71	75
Average	0.52	10.1	70	86	80.6	86

Table 2. Results of the Experiment in Rainy Weather

Timing	Avg. Response Time (s)	Avg. Response Distance (m)	Avg. Speed (Km/Hr.)	Recorded Traffic Offenses	No. of Received Messages	Offense-Detection Accuracy (%)
Morning	0.52	10.1	70	85	79	85
Afternoon	0.47	09.1	70	78	65	78
Evening	0.55	10.7	70	77	66	77
Night	0.60	11.7	70	65	62	65
Late Night	0.59	11.5	70	66	60	66
Average	0.55	10.6	70	74.2	66.4	74.2

The results show that the average accuracy of traffic-offense detection ranged between 74.2% and 84%, the average response time ranged between 0.52 and 0.55 seconds, the average response distance ranged between 10.08 and 10.62 meters, and the average number of received messages at the offender’s mobile phone ranged between 66.4 and 80.6. It is clear that the performance is better for sunny weather and day than for rainy weather and night respectively. Since the other two offenses related to over-speeding and prohibited stop areas are designed on the same concept, the results of these experiments can be generalized to these offenses that will be implemented and tested in future work and studies.

### SURVEY RESULTS

This subsection provides the results of the survey conducted with the target group of vehicle drivers that provided the specifications of the proposed system. Table 3 illustrates the distribution of the sample according to the gender variable, which indicates that males are dominant with a percentage of 96.4%, compared to 3.6% females.

Table 3. Distribution of the sample according to the gender

Gender	Frequency	Percentage	Actual Percentage	Cumulative Percentage
Males	108	96.4	96.4	96.4
Females	4	3.6	3.6	100.0
Total	112	100.0	100.0	

Table 4 depicts the distribution of the sample according to the age variable, where the percentage was 5.4% for those aged 20 years and under, 42.9% for those between the ages of 21-30, 23.2% for those aged 31-40, and 11.6% for those aged 50 years and over.

Table 4. Distribution of the sample according to the Age Group

Age Group	Frequency	Percentage	Actual Percentage	Cumulative Percentage
Below 20	6	5.4	5.4	5.4
21-30	48	42.9	42.9	48.2
31-40	26	23.2	23.2	71.4
41-50	19	17.0	17.0	88.4
More than 50	13	11.6	11.6	100.0
Total	112	100.0	100.0	

Table 5 indicates the distribution of the sample according to the educational level variable. Results showed that the percentage was 30.4% for those below high school, 25.0% for those who passed high school, and with regard to the intermediate diploma, the percentage was 3.6%, while 37.5% of the sample has a bachelor's degree, and 3.6% of the sample have postgraduate studies.

Table 5. Distribution of the sample according to the Level of Education

Level of Education	Frequency	Percentage	Actual Percentage	Cumulative Percentage
Below high school	34	30.4	30.4	30.4
High school	28	25.0	25.0	55.4
Intermediate diploma	4	3.6	3.6	58.9
Bachelor's degree	42	37.5	37.5	96.4
Postgraduate studies	4	3.6	3.6	100.0
Total	112	100.0	100.0	

In addition, figures 7-12 summarize the distribution of the sample on other variables. In summary, most of the participants were males aged 21-30 years old, below high school, or who had a bachelor's degree. The driver's profession was mostly divided between public and private transportation at 38% and 37%, respectively.

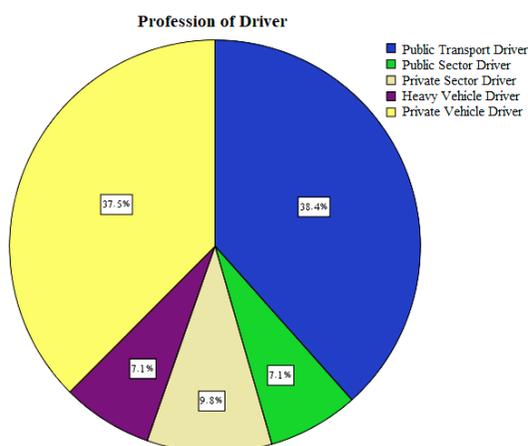


Figure 7 Profession of Driver

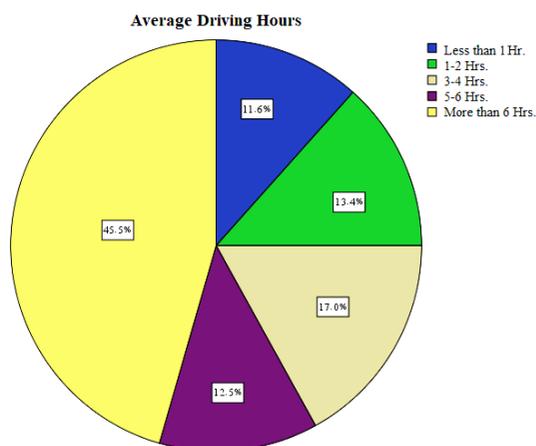


Figure 8 Average Driving Hours

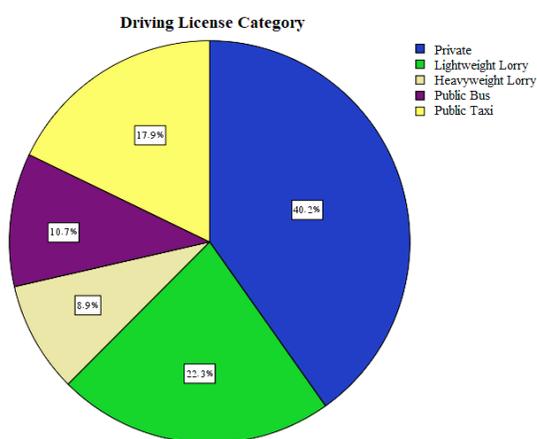


Figure 9 Driving License Category

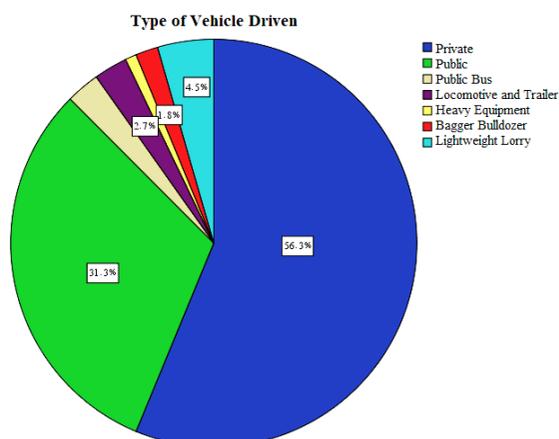


Figure 10 Type of Vehicle Driven

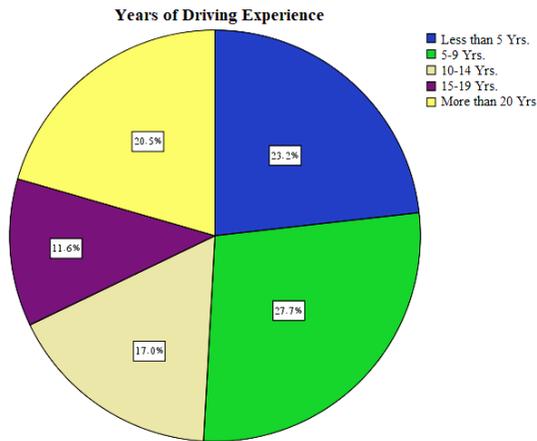


Figure 11 Years of Driving Experience

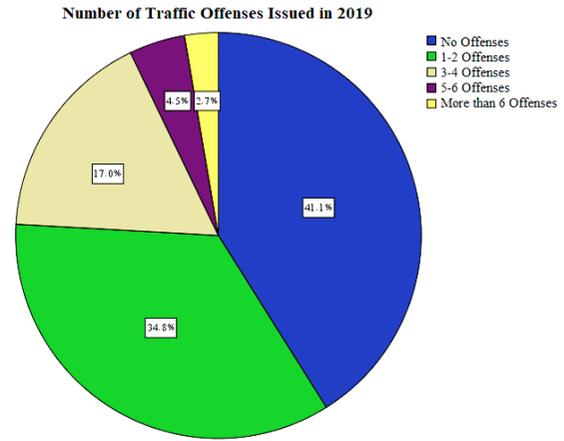


Figure 12 Number of Traffic Offenses Issued in 2019

The average daily driving hours were more than 6 hours for 45% of the sample, and the driving license category was mostly for private vehicles with 40%. Moreover, the vehicle type was mostly private (56%) or public (31%), and the driving experience was ranged 5-9 years (28%) and almost the same for drivers with less than 5 years (23%) or more than 20 years of experience (21%). However, 41% of the sample were not issued any traffic tickets in 2019, 35% were issued 1-2 tickets, and 17% of the drivers were issued 3-4 traffic-offense tickets.

properties, and 8% were in physical, material, and public properties.

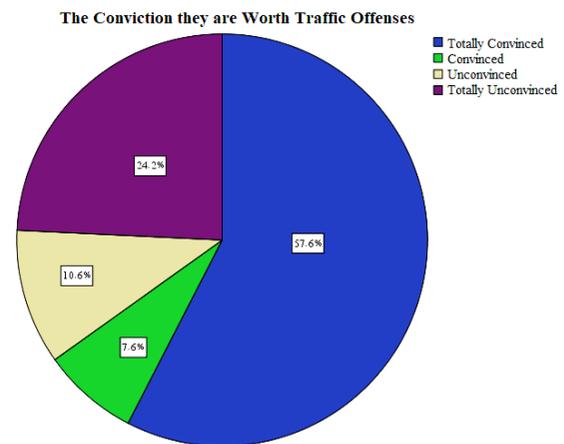


Figure 13 The Conviction they are Worth Traffic Offenses

Figures 13-18 indicate the distribution of the sample according to the following variables:

- The drivers are convinced that they deserved the issued traffic tickets: 57.6% were 'totally convinced', compared to 24% who were 'totally unconvinced'.
- Nature of Penalties: most of the penalties (95%) were based on fines.
- The appropriateness of the penalties against the traffic offenses: 58% were totally convinced with the penalties, against 29% who were totally unconvinced with them.
- Number of traffic accidents in 2019: 66% of the drivers did not cause any traffic accident, while 32% caused 1-2 traffic accidents.
- Causes of traffic accidents: 68% of the accidents were due to traffic offenses. Tables 6 provides more details on the causes of these accidents.
- The nature of the damages resulting from traffic accidents: 60% of them were material damages, 16% were physical and material damages, 13% were in material and public

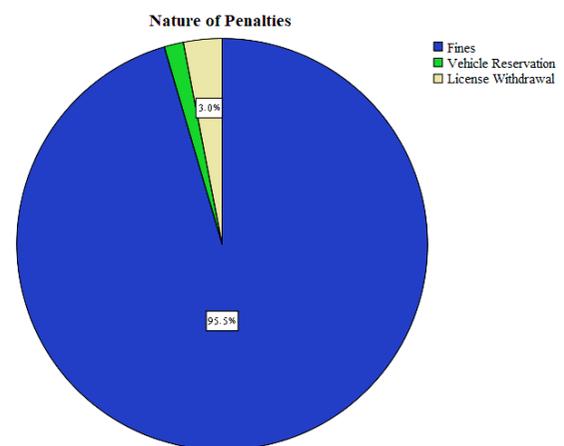


Figure 14 Nature of Penalties

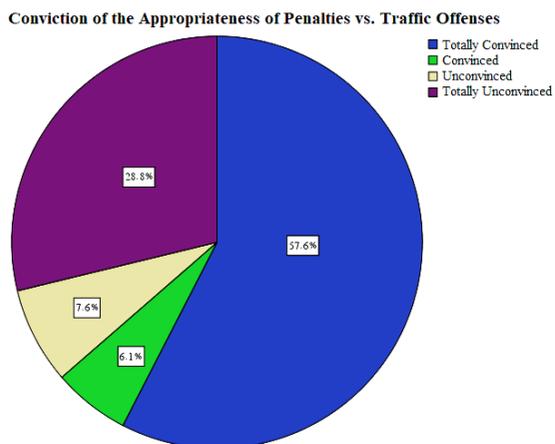


Figure 15 The Extent of Conviction of the Appropriateness of the Penalties vs. the Traffic Offenses

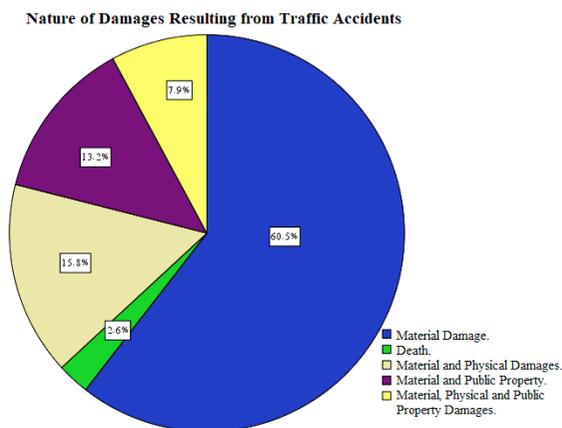


Figure 18 The Nature of Damages Resulting from Traffic Accidents

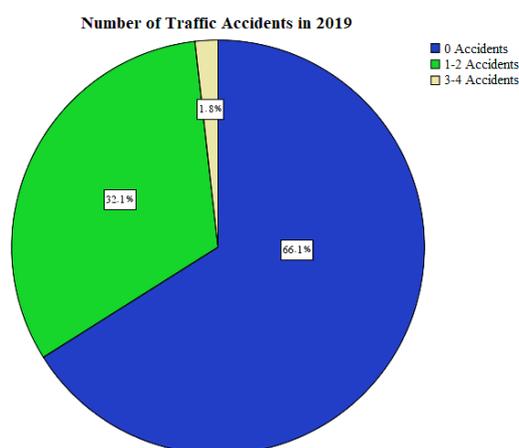


Figure 16 Number of Traffic Accidents in 2019

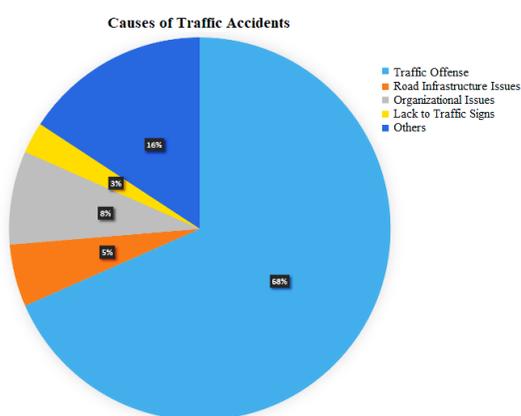


Figure 17 Causes of Traffic Accidents

Table 6. Causes of Accidents (Unifying Traffic Offenses)

Causes of Accidents, If any	Frequency	Percentage	Actual Percentage	Cumulative Percentage
Traffic tickets	26	23.2	68.4	68.4
Problems in the road infrastructure	2	1.8	5.3	73.7
Traffic regulation problems	3	2.7	7.9	81.6
Lack of traffic signs	1	0.9	2.6	84.2
Others	6	5.4	15.8	100.0
Total	38	33.9	100.0	
No accidents	74	66.1		
Total	112	100.0		

Detailed results of data analysis are listed in Appendix A (Tables 7-41). In summary, these tables show the results of the relationship between the traffic offenses tickets and traffic accidents variables, as well as the relationship between these two variables and the variables of gender, age group, educational level, profession, average daily driving hours, driving license category, type of the vehicle, and years of driving. It is noted that the significance level for all the variables is greater than 0.05. Thus, the relationship is not statistically significant. Therefore, the null hypothesis is valid; i.e., there is no relationship, except for three variables, as described below.

The first case is shown in Tables 24 and 25. Table 24 illustrates the distribution of the number of traffic tickets issued in 2019 on the average daily-driving hours. It shows that 2.6% of those who received 1-2 traffic tickets during the year 2019 drove for less than one hour on average. The same holds for members whose daily driving hours ranged between 1-2 hours. On the other hand, both tables revealed a steady increase in the number of offenses among individuals who drive more than 3 hours per day. Based on the Pearson correlation coefficient analysis in Table 25, it was found that the value of the significance level of 0.002 is less than 0.05. Therefore, the null hypothesis is

rejected, and we accept the alternative hypothesis; the relationship is statistically significant between the number of tickets issued during 2019 and the average daily driving hours. That is, an increase in the rate of daily driving hours leads to an increase in the number of traffic accidents. This could be attributed to the higher possibility of accidents due to the long driving hours or could be due to fatigue or zoning out during the long periods of driving.

The second case is shown in Tables 28 and 29, where the significance level equals 0.05, indicating a statistically significant relationship between the number of traffic tickets in 2019 and the driving license category. Most of the traffic tickets were issued, alternately, in 2019 for holders of private vehicle licenses and public service vehicle licenses.

The third case is shown in Tables 40 and 41, where there is a statistically significant relationship between the number of traffic tickets issued for the study sample in 2019 and the number of traffic accidents committed by them in the same year, with a significance level of 0.032, i.e., less than 0.05, so the null hypothesis is rejected.

## CONCLUSIONS AND RECOMMENDATIONS

This research objective has been achieved, and the concept has been proved. The proposed STMS was designed for three traffic offenses, running a red light, speeding, and parking in a prohibited parking space. In order to prove its importance and feasibility, the researcher conducted a survey using both quantitative and qualitative instruments. Results of both instruments show that the implementing proposed STMS is highly urgent to manage traffic congestion and accidents through monitoring and detection of traffic offenses in a smart way.

The researcher implemented and tested the first traffic offense in a testing environment designed for this purpose, including different times in the day and weather conditions. The proposed STMS proved an acceptable accuracy of traffic offense detection, which ranges between 74%-84% with different weather conditions.

However, in light of the obtained results and discussion, the researcher concludes the following recommendations for the traffic authorities:

1. They should apply stricter laws against those committing traffic offenses and balance

between the financial penalty and the nature of a traffic offense.

2. They are required to develop a similar integrated STMS that uses cameras, sensors, and radars to ensure the traffic laws' application and transparency.
3. They should develop the road's infrastructure accordingly and take into consideration the required substantial budget.
4. They should utilize the proposed STMS and its valuable features, e.g., it can inform the vehicle owner of any traffic offense that occurred while driving his/her vehicle by other people.

## ACKNOWLEDGEMENT

Research team would like to thank the Palestinian Ministry of Higher Education and Scientific Research for funding this research project through the Faculty of Graduate Studies and Scientific Research at Al-Quds Open University.

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## Appendix A

### Detailed Results of the Quantitative Instrument

Table 7 depicts the causes of traffic accidents, including the traffic offenses committed by drivers of the study sample.

**Table 7. Causes of Accidents (With Details of Traffic Offenses)**

Causes of Accidents, If Any	Frequency	Percentage	Actual Percentage	Cumulative Percentage
Traffic ticket	13	11.6	34.2	34.2
Problems in the road infrastructure	2	1.8	5.3	39.5
Traffic regulation problems	3	2.7	7.9	47.4
Lack of traffic signs	1	.9	2.6	50.0
Traffic tickets, speeding	11	9.8	29.0	79.0
Traffic tickets, seat belts	2	1.8	5.3	84.3
Others	6	5.4	15.8	100.0
Total	38	33.9	100.0	
No accidents	74	66.1		
Total	112	100.0		

The data in Table 8 refers to the distribution of the study sample according to the relationship between the number of traffic offenses issued in 2019 and the gender variables. The results showed that 91.3% of the study sample individuals who did not receive tickets were males compared to 8.7% of females. However, we found that all of the individuals who committed traffic offenses were males regardless of the number of offenses.

**Table 8. Relationship between the Number of Traffic Offenses Issued in 2019 and Gender**

Gender	Number of Traffic Offenses Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
Males	91.3%	100.0%	100.0%	100.0%	100.0%	96.4%
Females	8.7%					3.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Based on the Chi-square test (Pearson correlation coefficient) in Table 9, the value of the significance level is 0.203 that is greater than 0.05; thus, it is not statistically significant. Accordingly, we accept the null hypothesis that there is no relationship between the variable of the number of traffic offenses issued in 2019 and the gender variable.

**Table 9. Correlation between the Number of Traffic Offenses and Gender Variables (Chi-Square Test)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	5.952a	4	.203
Likelihood Ratio	7.333	4	.119
Linear-by-Linear Association	3.563	1	.059
N of Cases	112		

a. 7 cells (70.0%) have an expected count of less than 5. The minimum expected count is 11.

The data in Table 10 refers to the distribution of the study sample according to the relationship between the number of accidents in 2019 and the gender variables. It is noted that 94.6% of the study sample, who were not involved in accidents, were males, while 5.4% were females. It is also noted that all of the study sample's members, who had traffic accidents, were all males, regardless of the number of accidents in which they were involved.

**Table 10. Relationship between the Number of Accidents and Gender**

Gender	Number of Traffic Accidents in 2019			Total
	None	1-2	3-4	
Male	94.6%	100.0%	100.0%	96.4%
Female	5.4%			3.6%
Total	100.0%	100.0%	100.0%	100.0%

According to Table 11, the value of the significance level of 0.345 is greater than 0.05. Thus, it is not statistically significant. Therefore, the null hypothesis here is valid; there is no correlation between the number of accidents in 2019 and the gender variables.

**Table 11. Correlation between the Number of Accidents and Gender Variables**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.130 <sup>a</sup>	2	.345
Likelihood Ratio	3.391	2	.183
Linear-by-Linear Association	1.976	1	.160
N of Cases	112		

a. 4 cells (66.7%) have an expected count of less than 5. The minimum expected count is .07.

The data in Table 12 refers to the distribution of the study sample according to the relationship between the number of traffic offenses in 2019 and the age group variables. It is noted that 43.5% of the age group (21-30 years) did not commit any traffic offenses (the highest percentage among the study sample). On the other hand, only 6.5% of the age group (20 years and below) did not commit any traffic offenses (the lowest percentage among the study sample). However, it was

revealed that the highest percentages of traffic offenders are from the age group between 21-30 years, regardless of the number of offenses. On the other hand, the lowest percentages of traffic offenders are from the age group of 50 years and above (1-2 offenses), while those between 41-50 years committed 3-4 offenses and 6-5 offenses, and finally, the age group (50 years and above) had more than 6 offenses.

**Table 12. The Relationship between the Traffic Offense Tickets Received in 2019 and the Age Group**

Age Group	Number of Traffic Tickets Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
20 and below	6.5%	7.7%				5.4%
21-30	43.5%	43.6%	31.6%	60.0%	66.7%	42.9%
31-40	26.1%	23.1%	26.3%			23.2%
41-50	13.0%	20.5%	15.8%	40.0%		17.0%
50 and above	10.9%	5.1%	26.3%		33.3%	11.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

According to Table 13, it was found that the value of the significance level of 0.529 is greater than 0.05. Thus, it is not statistically significant. Therefore, the null hypothesis here is valid; there is no relationship between the number of offenses issued in 2019 and the age group variables.

**Table 13. The Correlation between the Number of Offenses Received in 2019 and the Age Group Variables.**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	14.941a	16	.529
Likelihood Ratio	17.829	16	.334
Linear-by-Linear Association	1.371	1	.242
No of Cases	112		

a. 17 cells (68.0%) have an expected count of less than 5. The minimum expected count is .16.

The data in Table 14 refers to the distribution of the study sample according to the relationship between the number of accidents in 2019 and the age group. It is noted that 40.5% of the age group (21-30 years) did not have any accident (the highest percentage), while 5.4% of the age group (20 and below) did not have any accident (the lowest percentage). On the other hand, 44.4% (the highest percentage) of those who had accidents in 2019 were from the age group (21-30) with (1-2 accidents). The age groups 20 years and below and 41-50 years had the lowest rate of accidents. Most of the accidents occurred among the age group of 21-30 years with 3-4 accidents.

**Table 14. Relationship between the Number of Accidents in 2019 and the Age Group Variable**

Age group	Number of Accidents in 2019			Total
	None	1-2	3-4	
20 and below	5.4%	5.6%		5.4%
21-30	40.5%	44.4%	100.0%	42.9%
31-40	20.3%	30.6%		23.2%
41-50	23.0%	5.6%		17.0%
50 and above	10.8%	13.9%		11.6%
Total	100.0%	100.0%	100.0%	100.0%

According to Table 15, it was found that the value of the significance level of 0.392 is greater than 0.05. Thus, it is not statistically significant. Therefore, we accept the null hypothesis; there is no relationship between the number of accidents in 2019 and the age group variables.

**Table 15. The Correlation between the Number of Accidents and the Age Group Variables.**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	8.434a	8	.392
Likelihood Ratio	9.914	8	.271
Linear-by-Linear Association	1.169	1	.280
No of Cases	112		

a. 8 cells (53.3%) have an expected count of less than 5. The minimum expected count is .11.

**Table 16. Relationship between the Number of Received Traffic Tickets in 2019 and the Academic Qualification.**

Academic Qualifications	Number of Traffic Tickets You Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
School Dropout	23.9%	33.3%	42.1%	20.0%	33.3%	30.4%
High School Diploma	23.9%	23.1%	31.6%	20.0%	33.3%	25.0%
Intermediate Diploma	6.5%			20.0%		3.6%
Bachelor	39.1%	41.0%	26.3%	40.0%	33.3%	37.5%
Postgraduate	6.5%	2.6%				3.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

**Table 17. Correlation between the Number of Traffic Tickets and the Academic Qualifications)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	12.426a	16	.714
Likelihood Ratio	13.180	16	.660
Linear-by-Linear Association	1.824	1	.177
N of Cases	112		

a. 17 cells (68.0%) have an expected count of less than 5. The minimum expected count is .11.

**Table 18. Relationship between the Number of Traffic Accidents in 2019 and the Academic Qualification**

Academic Qualification	Number of Traffic Accidents You Had in 2019			Total
	None	1-2	3-4	
School Dropout	33.8%	25.0%		30.4%
High School Diploma	24.3%	25.0%	50.0%	25.0%
Intermediate Diploma	1.4%	8.3%		3.6%
Bachelor	36.5%	38.9%	50.0%	37.5%
Postgraduate	4.1%	2.8%		3.6%
Total	100.0%	100.0%	100.0%	100.0%

**Table 19. Correlation between the Number of Accidents and the Academic Qualifications)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	5.431a	8	.711
Likelihood Ratio	5.765	8	.674
Linear-by-Linear Association	.542	1	.462
No of Cases	112		

a. 9 cells (60.0%) have an expected count of less than 5. The minimum expected count is .07.

**Table 20. Relationship between the Number of Traffic Tickets Issued in 2019 and the Profession of the Driver**

Profession	Number of Traffic Tickets You Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
Public Transport Driver	23.9%	33.3%	78.9%	60.0%	33.3%	38.4%
Public Sector Driver	10.9%	7.7%				7.1%
Private Sector Driver	8.7%	12.8%	5.3%	20.0%		9.8%
Heavy Equipment Driver	8.7%	10.3%				7.1%
Private car Driver	47.8%	35.9%	15.8%	20.0%	66.7%	37.5%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

**Table 21. Correlation between the Number of Traffic Tickets and the Profession of the Driver**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	23.444a	16	.102
Likelihood Ratio	26.244	16	.051
Linear-by-Linear Association	6.219	1	.013
No of Cases	112		

a. 19 cells (76.0%) have an expected count of less than 5. The minimum expected count is .21

**Table 22. Relationship between the Number of Accidents in 2019 and Profession of the Driver**

Academic Qualification	Number of Traffic Accidents in 2019			Total
	None	1-2	3-4	
Public Transport Driver	36.5%	44.4%		38.4%
Public Sector Driver	8.1%	5.6%		7.1%
Private Sector Driver	12.2%	5.6%		9.8%
Heavy Equipment Driver	8.1%	2.8%	50.0%	7.1%
Private car Driver	35.1%	41.7%	50.0%	37.5%
Total	100.0%	100.0%	100.0%	100.0%

**Table 23. Correlation between the Number of Traffic Accidents and the Profession of the Driver**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	9.384a	8	.311
Likelihood Ratio	7.891	8	.444
Linear-by-Linear Association	.145	1	.704
No of Cases	112		

a. 8 cells (53.3%) have an expected count of less than 5. The minimum expected count is .14

**Table 24. Relationship between the Number of Traffic Tickets in 2019 and the Average Daily Driving Hours**

Average Daily Driving Hours	Number of Traffic Tickets You Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
Less than one hour	23.9%	2.6%			33.3%	11.6%
1-2 hours	26.1%	2.6%	5.3%	20.0%		13.4%
3-4 hours	13.0%	28.2%	5.3%	20.0%		17.0%
5-6 hours	6.5%	15.4%	15.8%	20.0%	33.3%	12.5%
More than 6 hours	30.4%	51.3%	73.7%	40.0%	33.3%	45.5%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

**Table 25. Correlation between the No. of Traffic Tickets and the Average Daily Driving Hours**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	37.628a	16	.002
Likelihood Ratio	41.337	16	.000
Linear-by-Linear Association	10.336	1	.001
No of Cases	112		

a. 16 cells (64.0%) have an expected count of less than 5. The minimum expected count is .35.

**Table 26. Relationship between the Number of Accidents in 2019 and the Average Daily Driving Hours**

Average Daily Driving Hours	Number of Traffic Accidents in 2019			Total
	None	1-2	3-4	
Less than one hour	16.2%	2.8%		11.6%
1-2 hours	13.5%	11.1%	50.0%	13.4%
3-4 hours	17.6%	16.7%		17.0%
5-6 hours	9.5%	16.7%	50.0%	12.5%
More than 6 hours	43.2%	52.8%		45.5%
Total	100.0%	100.0%	100.0%	100.0%

**Table 27. Correlation between the Number of Accidents and the Average Daily Driving Hours**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	11.211a	8	.190
Likelihood Ratio	11.807	8	.160
Linear-by-Linear Association	2.001	1	.157
N of Cases	112		

a. 8 cells (53.3%) have an expected count of less than 5. The minimum expected count is .23.

**Table 28. Relationship between the Number of Traffic Tickets Received in 2019 and the License Category.**

License Category	Number of Traffic Tickets Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
Private	47.8%	41.0%	21.1%	20.0%	66.7%	40.2%
light truck	28.3%	17.9%	10.5%	40.0%	33.3%	22.3%
Heavy truck	10.9%	12.8%				8.9%
Public bus	6.5%	10.3%	21.1%	20.0%		10.7%
Taxi	6.5%	17.9%	47.4%	20.0%		17.9%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

**Table 29. Correlation between the Number of Received Traffic Tickets and License Category)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	26.318a	16	.050
Likelihood Ratio	27.728	16	.034
Linear-by-Linear Association	6.014	1	.014
N of Cases	112		

a. 18 cells (72.0%) have an expected count of less than 5. The minimum expected count is .27.

**Table 30. Relationship between the Number of Accidents and the License Category**

License Category	Number of Traffic Accidents You Had in 2019			Total
	None	1-2	3-4	
Private	40.5%	38.9%	50.0%	40.2%
light truck	24.3%	19.4%		22.3%
Heavy truck	10.8%	2.8%	50.0%	8.9%
Public bus	9.5%	13.9%		10.7%
Taxi	14.9%	25.0%		17.9%
Total	100.0%	100.0%	100.0%	100.0%

**Table 31. Correlation between the Number of Accidents and the License Category)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	8.794a	8	.360
Likelihood Ratio	8.267	8	.408
Linear-by-Linear Association	.686	1	.408
No of Cases	112		

a. 7 cells (46.7%) have an expected count of less than 5. The minimum expected count is .18.

**Table 32. Relationship between the Number of Traffic Tickets Received in 2019 and the Vehicle Type**

Vehicle Type	Number of Traffic Tickets Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
Private	67.4%	59.0%	26.3%	40.0%	66.7%	56.3%
Public	17.4%	25.6%	68.4%	60.0%	33.3%	31.3%
Public bus	2.2%	2.6%	5.3%			2.7%
Cargo truck	4.3%	2.6%				2.7%
Operating engineers	2.2%					0.9%
Bulldozer	2.2%	2.6%				1.8%
Commercial and light truck	4.3%	7.7%				4.5%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

**Table 33. Correlation between the Number of Traffic Tickets and the Type of Vehicle)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	23.475a	24	.492
Likelihood Ratio	24.936	24	.409
Linear-by-Linear Association	.163	1	.686
No of Cases	112		

a. 29 cells (82.9%) have an expected count of less than 5. The minimum expected count is .03.

**Table 34. Relationship between the Number of Traffic Accidents in 2019 and the Vehicle Type**

Vehicle Type	Number of Traffic Accidents in 2019			Total
	None	1-2	3-4	
Private	56.8%	55.6%	50.0%	56.3%
Public	28.4%	38.9%		31.3%
Public bus	2.7%	2.8%		2.7%
Cargo truck	2.7%	2.8%		2.7%
Operating engineers	1.4%			0.9%
Bulldozer	2.7%			1.8%
Commercial and light truck	5.4%		50.0%	4.5%
Total	100.0%	100.0%	100.0%	100.0%

**Table 35. Correlation between the Number of Traffic Accidents and the Type of Vehicle)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	14.207a	12	.288
Likelihood Ratio	11.162	12	.515
Linear-by-Linear Association	.102	1	.749
N of Cases	112		

a. 17 cells (81.0%) have an expected count of less than 5. The minimum expected count is .02.

**Table 36. Relationship between the Number of Traffic Tickets Issued in 2019 and the Years of Driving**

Years of Driving	Number of Traffic Tickets You Received in 2019					Total
	None	1-2	3-4	5-6	More than 6	
Less than 5	39.1%	12.8%	5.3%	20.0%	33.3%	23.2%
5-9	17.4%	41.0%	26.3%	40.0%		27.7%
10-14	8.7%	20.5%	31.6%		33.3%	17.0%
15-19	13.0%	10.3%	10.5%	20.0%		11.6%
More than 20	21.7%	15.4%	26.3%	20.0%	33.3%	20.5%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

**Table 37. Correlation between the Number of Traffic Tickets and Years of Driving**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	22.770a	16	.120
Likelihood Ratio	25.120	16	.068
Linear-by-Linear Association	1.578	1	.209
No of Cases	112		

a. 15 cells (60.0%) have an expected count of less than 5. The minimum expected count is .35.

**Table 38. Relationship between the Number of Accidents in 2019 and Years of Driving**

Years of Driving	Number of Traffic Accidents in 2019			Total
	None	1-2	3-4	
Less than 5	25.7%	16.7%	50.0%	23.2%
5-9	24.3%	33.3%	50.0%	27.7%
10-14	14.9%	22.2%		17.0%
15-19	10.8%	13.9%		11.6%
More than 20	24.3%	13.9%		20.5%
Total	100.0%	100.0%	100.0%	100.0%

**Table 39. Correlation between the Number of Accidents and Years of Driving)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	5.808a	8	.669
Likelihood Ratio	6.637	8	.576
Linear-by-Linear Association	.657	1	.418
No of Cases	112		

a. 6 cells (40.0%) have an expected count of less than 5. The minimum expected count is .23.

**Table 40. Relationship between the Number of Traffic Tickets and the Number of Accidents in 2019**

No of Traffic Tickets Received in 2019	Number of Traffic Accidents in 2019			Total
	None	1-2	3-4	
none	50.0%	22.2%	50.0%	41.1%
1-2	33.8%	36.1%	50.0%	34.8%
3-4	8.1%	36.1%		17.0%
5-6	5.4%	2.8%		4.5%
More than 6	2.7%	2.8%		2.7%
Total	100.0%	100.0%	100.0%	100.0%

**Table 41. Correlation between the Number of Traffic Tickets and the Number of Accidents in 2019)**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	16.823a	8	.032
Likelihood Ratio	16.753	8	.033
Linear-by-Linear Association	3.952	1	.047
No of Cases	112		

a. 9 cells (60.0%) have an expected count of less than 5. The minimum expected count is .05.