**Developing a Smart Traffic Management System for the Palestinian Cities**

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**Abstract**

This research paper emerged from the urgent need to address traffic offenses and the accompanying accidents, and to 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 increases the government income and reduces the risk of traffic accidents resulting from offenses.

**Keywords**: Traffic Offenses, Traffic Accidents, Issuing e-Tickets, Traffic Management System, Track and Detect Offenses, Fines, Running a Red Light.

**تطوير نظام ذكي لإدارة السير وتنظيم المرور في المدن الفلسطينية**

**ملخص**

تنبع فكرة المشروع البحثي من الحاجة الماسة إلى معالجة مشكلة مخالفات السير وضبط أنظمة المرور، وتقليل الازدحانات الخانقة. إذ يسهم النظام ويخدم الجهات المختصة (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 رئيسة 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 لمرتكبيها، تصلهم عبر رسالة قصيرة تحدد وقت المخالفة وطبيعتها وغرامتها، لمنعهم من ارتكابها مرة أخرى. كما يوفر نموذجًا لمراقبة الازدحام المروري والتحكم بزمن 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 الإفادة من نتائج البحث في تعميمها ونشرها، إضافة إلى تحديد المعيقات 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**: مخالفات المرور، الحوادث المرورية، إصدار مخالفات إلكترونية، نظام إدارة المرور، كشف المخالفة ورصدها وتنفيذها، الغرامات، تجاوز الإشارة الحمراء.

**Acknowledgement**

I would like to thank the Palestinian Ministry of Higher Education and Scientific Research for funding this research project, and the Faculty of Graduate Studies and Scientific Research at Al-Quds Open University for selecting my proposal for fund.

# 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 hazardous road accidents has increased steadily, causing a significant loss in lives, public and private properties. To address this issue, this paper was set out to find suitable solutions through employing the concept of smart cities, mainly the Internet of Things (IoT), in order to regulate and manage traffic. The proposed system serves the competent authorities, which are the traffic department and traffic police. This research aims to design and build a Smart Traffic Management System (STMS) that integrates hardware components such as cameras and sensors to control traffic congestion and detect traffic offenses. The detected offenses are recorded on a central database, their e-tickets are issued and sent to the offenders using a SMS server. Accordingly, this paper aims to monitor, control, treat traffic congestions, detect traffic offenses, and reduce damages of public and private properties and loss of people’s lives resulting from traffic accidents to deter drivers from recurring such offenses, hence acquaint them with the consequences.

The essential national benefit of the proposed STMS stem from setting out precautions that minimize the risks and traffic accidents resulted from offenses, as a first stage to reach Palestinian smart cities in the future. The proposed STMS automatically detects different types of offenses, such as speeding, parking in a prohibited space, running a red light, etc. The system is designed to accurately issue e-tickets as part of automated and integrated procedures. System sustainability is granted through which offense fines are collected, especially those lost ones resulting from undetected offenses. In fact, there is a large number of offenses that are not currently detected due to the lack of human resources or the circumvention of drivers from paying the fines. Accordingly, the proposed STMS will be able to monitor such kinds of situations and behaviors, in addition to traffic-congestion control.

This research is limited to three traffic offenses, including running a red light, over-speeding and parking in prohibited public places in Ramallah and al-Bireh governorate. In addition, it provides a traffic monitoring system for congestion control at traffic signals. 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 governorate, where a sample was selected to complete the data collection instruments, mainly, questionnaires and interviews to collect the opinions of drivers, beneficiaries and related parties. Results of the research were based on quantitative and qualitative data analysis for both research instruments, as well as the prototype testing results.

# Background

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 are 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 to 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).

**Running red lights:** To detect red light traffic offense, the STMS functions in two approaches. The first cost-effective approach is based on input from a laser sensor to an Arduino that calculates the distance between the traffic light and the vehicle that when exceeding a specific limit, the plate number is extracted from a memory attached to a transmitter in the vehicle. Then, the transmitter sends the number to a receiver attached to the traffic light that is connected to a central database through Wi-Fi or 3G. The second is based on a smart camera attached to the traffic light that operates when the light color is altered to red. When a vehicle runs the red light, its plate number is detected through image processing. In both cases, a query is generated using the plate number and sent to a central database to obtain the owner’s contact information. The STMS issues an e-ticket indicating the traffic offense type, time and fine value, and sends it to the owner and the competent authorities (Anati, 2016).

**Over-speeding:** In this case, a vehicle speed sensor and a GPRS are embedded on the vehicle to detect its speed compared with the speed limit of that location, 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 (Anati, 2016).

**Prohibited Parking:** The STMS employs a QR code reader embedded in the vehicle that extarcts information from a QR code on the sidewalk of prohibited parking area, 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 (Anati, 2016).

# 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 developing a STMS that uses cameras, sensors and radars, to ensure the application and transparency of the traffic law, refering that traffic offenses are the major reason for traffic accidents. However, this requires suitable infrastructure and sufficient allocated budget. They also suggested that the STMS should be able to inform the vehicles’ owners of any offenses occured 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. *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.

# Methodology

The research methodology was based on a survey on the value and applicability of the developed prototype, which employed quantitative and qualitative instruments for data collection after testing it on a sample of public vehicles for this purpose. These instruments include:

1. A questionnaire designed and completed by a sample of drivers to measure the degree of the STMS applicability and its ability to detect traffic offenses.
2. Personal interviews conducted with a sample of drivers and senior management in the traffic department at the Ministry of Transportation and the traffic police in Palestine.

As indicated previously, the first method entailed conducting a survey on the opinions of the target group using questionnaires and interviews. The data were collected and analyzed using the appropriate qualitative and quantitative data analysis tools based on thematic coding and SPSS respectively. In contrast, the second method included building and developing a prototype to be applied, operated and tested in some selected locations, paving the way for building a comprehensive and a broader system in the future studies if sufficient funding can be allocated.

# Literature Review

As part of the global smart-city agenda, digital technologies became the backbone of smart cities to enhance quality of service in urban infrastructure. 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 environment is the most efficient way to constitute the 21st century’s ideal cities. The smart city transport concept is considered as a future vision aiming to investigate the urban planning process and to construct policy-pathways to achieve the 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 Intelligent Transportation System (ITS) and smart cities is the Traffic Management System (TMS). The ITS collects traffic-related data that enable travelers to select travelling modes and paths and departure time. 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 the 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 snapshoot the plate number of the offender’s vehicle using AMCap application. The plate’s image is sent to the monitoring device, and is displayed on a special webpage with 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 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 field (Angeline, Aswini, Devadharshini, Gousalya, & Aravind, 2018). This technique can be used by traffic monitoring systems or police to identify the vehicle using a RFID reader that provide 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 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 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 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 managemenet techniques, Das, Dash and Mishra (2018) developed a 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 cross road signal, using 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 on a traffic light (Abdulmunem, 2015).

A STMS has been applied in China to help the police deal with traffic offenses and accidents quickly and reduce traffic jam, 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). 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 cause 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 that are analyzed accurately in order 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 in 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. A new technology 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 the help of cameras and sensors of pressure and temperature, and regulates 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 12 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 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 that have traffic signals and helps the vehicles to 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 driver of the emergency vehicle 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 proposed 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 includes prevention, detection, recording, and ticket issuance and execution.

# The Proposed STMS

The researcher developed a prototype for the proposed STMS following the system development lifecycle in four phases, system 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.

* 1. **System Analysis and Requirements**

In order to specify the system requirements, the researcher conducted semistructured personal interviews with 44 drivers of various types of vehicles. The data were analyzed through coding, classification, and extracting results. This analysis took the sahape of needs assessment in three domains: The current status, the target status, and bridging the gap between them. In addition, a s ample of 102 drivers completed a quantitative survey related to the problems of the current traffic management system in Palestine.

* + 1. **The current status**

Following the analysis of the participants’ responses, the following points were concluded on the current status of the traffic system in Palestine:

1. Lack of a smart technical traffic system that uses cameras, sensors, and surveillance devices. Moreover, slow procedures for detecting and addressing traffic offenses prevail in the current system.
2. Unjust application of the traffic laws. When drivers commit traffic offenses, favoritism play a role in executing the law. This sometimes leads to voiding traffic tickets. Moreover, vehicles with Israeli plates are not accountable under the Palestinian traffic law.
3. In some areas, the lack of police presence allows drivers to change routes from main roads to bystreets, where police are usually not present.
4. Lack of sufficient awareness among the relevant authorities on traffic laws and systems.
5. Some traffic police officers lack to experience in traffic laws, traffic offenses, and accident assessment, who require further training for accurate decisions.
6. The penalties imposed on the drivers for committing traffic offenses are not deterrent. Therefore, more severe penalties need to be applied.
7. Police presence on the roads on a regular basis contributes to reducing attempts of traffic offenses. Thus, accidents and their consequences become less prevalent.
8. Drivers committing traffic offenses tend to deny them on the scene and argue with the police officer on the validity of the offenses, providing false excuses. The absence of surveillance devices, such as cameras, makes it more difficult for police officers to prove the offenses.
9. Offenses are the major cause of traffic accidents and congestion in cities, such as prohibited parking and overtaking, as well as driving against the lane flow.
10. The current system’s efficiency in deterring those drivers committing traffic offenses ranges between weak and medium deterrent.
    * 1. **The target status**

Through qualitative analysis of the answers of the interviews’ participants regarding the target status of the proposed STMS, the following points were concluded:

1. The goal of implementing the proposed STMS is to regulate traffic and reduce traffic offenses and accidents by enacting fair deterrent laws.
2. Prevention of using illegal vehicles, and periodic check of license and insurance validity.
3. Promotion of traffic awareness programs among citizens and drivers.
4. The STMS issues penalties for traffic offenders for compensation of material losses that result from traffic offenses and accidents.
5. Implementation of an advanced TMS that uses cameras to detect traffic offenses automatically without a constant need for police interventions.
6. Traffic police patrols should be present around the clock to monitor traffic jams and offenses.
7. Promotion of transparency and integrity by traffic police and enacting laws related to pleas in courts to rationalize penalties.
8. The participants disagreed on the relevance of the financial penalties to the nature of the offenses. Almost half of the participants indicated that they are appropriate, while the other half viewed it as inappropriate (either more or less than the actual value).
   * 1. **Bridging the gap**

According to the participants’ responses, the following points were suggested to bridge the gap between the current and target status:

1. The need for applying stricter laws against those committing offenses, such as revoking the license and seizing the vehicle, instead of relying only on the financial penalties, which are not deterrent to many high earners.
2. Evaluating the relevance of the offense fines to the nature of the offenses, and applying suitable penalties.
3. The need to inform the vehicle owner of any offense that occurs while driving his/her vehicle by other people in order to take the needed precautions.
4. The need for developing an integrated electronic smart system that uses cameras, sensors and radars, to ensure the application and transparency of the law. However, this requires suitable infrastructure and substantial budget.

Moreover, the quantitative instrument results based on the current traffic system, which will be more illborated in subsection 7.2, yield the following issues:

* Quarter of the drivers (24%) were totally unconvinced that they deserved the traffic tickets for their offenses issued in 2019.
* Most of the offense penalties (95%) were based on fines, where 29% of traffic offenders were totally unconvinced with these penalties.
* One third of the drivers (32%) caused 1-2 traffic accidents in 2019, where more than two thirds of these accidents (68%) were due to traffic offenses, causing physical and material damages, as well as losses in people lives and public properties.
* There was a steady increase in the number of traffic offenses issued in 2019 among drivers who usually drive more than 3 hours per day, mainly due to fatigue or zoning out.
* Most of the traffic tickets were for holders of private vehicle and public service vehicle licenses.
* There was a significant relationship between the number of traffic tickets issued in 2019 and the number of traffic accidents committed by them.

In summary, there is a mass need to develop the Palestinian TMS to overcome the mentioned issues, and to help the the traffic authorities in monitoring and management of traffic offenses in Palestine.

* 1. **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 sensors 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 and collects data from cameras and sensors such as laser, speed and magnetic sensors. 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. 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.

Traffic-Offense Recording Unit

Centralized Database

(Traffic Authority)

Messaging Server (SMS)

Traffic Management and Congestion Control Unit

Main Processing and Control Unit

Traffic Light Signal Module

Vehicle Identification Unit

Traffic-Monitoring Unit

Cameras/ Plate Shot Module

Traffic Sensor Module

Connection Unit

Internet

Figure . Block Diagram of the Proposed STMS

Sensor Control

Arduino

Speed Sensor

Laser Sensor

Magnetic Sensor

Data Collection

Data Analysis

Main Processing Unit

Raspberry Pi

Figure . Traffic-Sensor Module

Main Processing Unit

Raspberry Pi

GSM-3G/4G/

Ethernet

Internet

Issue Traffic Offense e-Ticket

Centralized Database Server

Messaging/ Mail Server

Insert Traffic Offense Record

Internet

Send Message to Driver

Figure . Traffic-Offense Recording Unit

**Main Processing Unit**

**Raspberry Pi**

NRF 2.4 GHz Module

**Vehicle ID Controller**

RFID Module

RF 433 MHz Module

Figure . Vehicle ID Unit (RF Module)

Main Processing Unit

Raspberry Pi

Switch Camera ON

Get Plate Snapshot

Switch Laser Sensor ON

If Traffic Signal = RED

Recognize Vehicle ID

Pair with Vehicle ID Controller

If traffic offense is detected

Figure . Traffic Monitoring Unit (Traffic-Offense Detection)

Figure 6 shows the Entity-Relationship Diagram (ERD) of the police centralized database of the proposed STMS, which describes the relation among the main entities and shows each entity’s main attributes. The ERD illustrates six entities with vehicle ID as the primary key, and each has its foreign key. The first entity identifies vehicles and has three additional 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). It has 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, and has 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. Each has a description attribute.



Figure . Entity Relationship Diagram (ERD) of the proposed STMS

* 1. **STMS Implementation**

Figure 7 shows a block diagram of the implemented case of our proposed STMS related to crossing red signals. 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. 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.

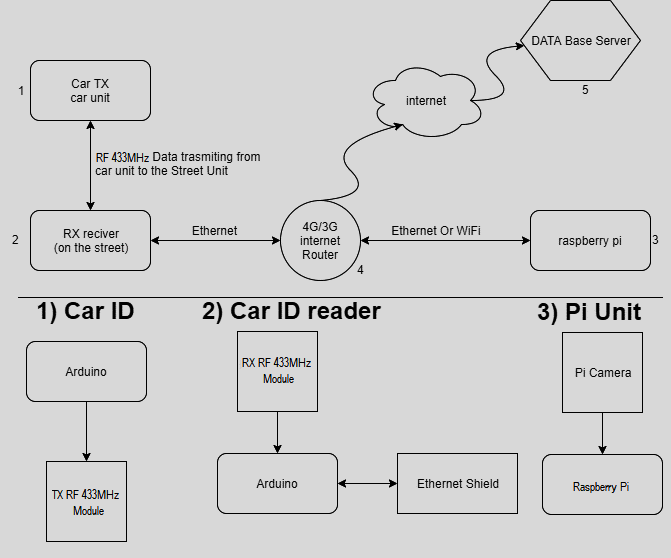


Figure . The Case of Running Red Light Offense Detection using Pi Camera.

As shown in Figure 7, the prototype consists of three 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.

When the traffic signal lights are red, and the vehicle passes over the Arduino installed on the street and connected to a RX RF 433 MHz receiver module, the TX RF 433MHz transmitter installed inside the vehicle sends its ID number to the receiver. Then, the Arduino creates a TCP connection with the Raspberry Pi through the Internet connection module and sends the information to it, so the Raspberry Pi turn on the camera and capture 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 vehicles 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 results of the system testing 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.

* 1. **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 fund 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 on 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. Experiments 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 the future work and studies.

* 1. **Survey Results**

This subsections 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 8-13 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 had bachelor degree. The driver’s profession was mostly divided between public and private transportation at 38% and 37% respectively. 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.

|  |  |
| --- | --- |
| Figure 9. Profession of Driver | Figure 10. Average Driving Hours |
| Figure 11. Driving License Category | Figure 12. Type of Vehicle Driven |
| Figure 13. Years of Driving Experience | Figure 14. Number of Traffic Offenses Issued in 2019 |

|  |  |
| --- | --- |
|  |  |
| Figure 15. The Conviction they are Worth Traffic Offenses | Figure 16. Nature of Penalties |
| Figure 17. The Extent of Conviction of the Appropriateness of the Penalties vs. the Traffic Offenses | Figure 18. Number of Traffic Accidents in 2019 |

|  |  |
| --- | --- |
| Figure 19. Causes of Traffic Accidents | Figure 20. The Nature of Damages Resulting from Traffic Accidents |

Figures 14-19 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 properties, and 8% were in physical, material and public properties.

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.

# Conclusion and Recommendation

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.

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**Appendix A**

**Detailed Results of the Quantitative Instrument**

Table 5 depicts the causes of traffic accidents, including the traffic offenses committed by drivers of the study sample.

Table . 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 6 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 . 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 7, 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 . 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 9 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 . Relationship between the Number of Accidents and Gender

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

According to Table 10, 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 . Correlation between the Number of Accidents and Gender Variables

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Value** | **df** | **Asymp. Sig.**  **(2-sided)** |
| Pearson Chi-Square | 2.130a | 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 10 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 . The Relationship between the Traffic Offense Tickets Received in 2019 and the Age Group

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

According to Table 11, 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 . 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 12 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 . Relationship between the Number of Accidents in 2019 and the Age Group Variable

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

According to Table 13, 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 . 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 . Relationship between the Number of Received Traffic Tickets in 2019 and the Academic Qualification.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table . 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.