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E-TRAVIO: A Web System Analytics with Prescriptions for Traffic Management in Local Government Unit

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Abstract*: Traffic violations remain a pressing concern in many municipalities, particularly due to outdated enforcement systems and inefficient monitoring methods. In response to these challenges, this study developed and evaluated E-TRAVIO, a web-based analytics system with prescriptions for managing traffic violations in local government units. The system aimed to digitize and centralize the monitoring, reporting, and enforcement of traffic rules, offering features such as real-time violation tracking, automated penalty assignment, geo-spatial mapping, and analytics reporting. A key innovation was the integration of a Decision Tree-based model to intelligently assign apprehending officers based on violation hotspots and officer performance data. The system was developed using Agile methodology and assessed through ISO 25010 software quality standards and the Technology Acceptance Model (TAM). Evaluation results indicated that E-TRAVIO achieved high scores in functionality, usability, and overall acceptability among its users, which included traffic management personnel and TODA drivers in Siniloan, Laguna. Despite some limitations—such as dependence on internet connectivity and manual data entry—the system was proven effective in enhancing traffic enforcement accuracy and efficiency. E-TRAVIO was shown to streamline violation processing, improve transparency, and enable data-driven decisions for traffic authorities. It provided users with clear access to violation history, real-time updates, and automated officer scheduling. The study concludes that the E-TRAVIO system is a reliable and scalable solution for municipalities aiming to modernize traffic enforcement through intelligent automation and real-time analytics.

***Keywords*: Decision Tree, Geo-Spatial Mapping, Prescriptive Analytics, Traffic Management.**

1. Introduction

A. Background of the Study

Traffic control is becoming more important around the world, especially in cities and places where more people drive and break the law, which causes crashes, traffic jams, and officers that don't do their jobs well (Smith & Tan, 2021; Kumar et al., 2020). Everyone knows that bad traffic systems can make things worse. Tan et al. (2021) say that these problems can be solved by new tools that make it easier to keep an eye on people and enforce the law. A modern traffic control system helps apprehension officers do their work, keeps people safe, and improves traffic flow (Chowdhury et al., 2021).

Things have changed a lot in the last few years when it comes to traffic and how officers use technology. Smart Transportation Systems (ITS) are used all over the world these days. These systems use AI, smart traffic signal control, CCTV surveillance, and real-time traffic tracking to make roads safer and traffic flow more smoothly (Tan et al., 2021). Technology like these is meant to make it easier to follow the rules of the road, so people will be less likely to break them (Kumar et al., 2020). Some examples are traffic systems in the US, South Korea, and Singapore that are run by AI. These systems allow for real-time research and can automatically spot people who break the rules. Not as many car accidents happen because more people are following the rules (Smith & Tan, 2021; World Economic Forum, 2022).

More and more traffic violations are still making it hard for cities around the world. These violations lead to traffic jams, accidents, and problems with the enforcers. Even though traffic rules are very strict, many cities have trouble stopping people who don't follow them. The World Health Organization (WHO) says that about 1.19 million people die every year in car accidents. Many of these deaths are directly caused by traffic violations and not following safety rules (WHO, 2020). Furthermore, studies show that people who don't follow the rules of the road are a major cause of road safety problems. This makes the urgent need for stricter enforcement methods even stronger. Meanwhile, enforcement of traffic laws and careless driving are still major problems that threaten city transportation systems (PMC, 2024).

Traffic violations are still a big problem in Istanbul when it comes to road safety. In 2024, 126,229 drivers were fined for going over the speed limit, 28,702 cars were fined for not having regular inspections, and 25,353 drivers were fined for not wearing seat belts. These numbers show how hard it is to keep traffic order and make sure people follow the rules (Daily Sabah, 2024).

For instance, in the United States, places like New York City and Chicago have a lot of traffic violations, which cost a lot of money. In 2024, New York City drivers often broke the law by

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speeding, running red lights, and parking illegally. These violations have a big impact on road safety and cost the city money. Penalties, higher insurance rates, and more work for the government are all consequences of these violations. A report from NBC New York in 2024 says that these violations contributed to the city's overall economic losses of about $9.5 billion.

Paid and unpaid traffic fines are a big part of managing traffic around the world. They have a big effect on road safety, how well laws are enforced, and how well people follow the rules. In well-developed systems, fines help pay for upkeep on infrastructure, tools for law enforcement, and systems that watch traffic (World Bank, 2020). In Singapore and South Korea, they use Intelligent Transportation Systems (ITS) that are combined with automated fine collection and analytics. This makes processes faster and increases the number of people who follow the rules (Land Transport Authority, 2021; Smith & Tan, 2021). In the US, AI-powered traffic regulation and real-time tracking of violations have made people more likely to follow the rules, which has cut down on accidents and made things easier for the government (World Economic Forum, 2022). A lot of traffic fines aren't paid in many developing or transitioning countries, though, because they don't have the right digital infrastructure or strong apprehension systems. This costs money and doesn't work as well to stop people from breaking the law (WHO, 2023; PMC, 2023). To deal with unpaid fines around the world, it needs to combine centralized databases, automated systems, and public awareness efforts to make sure everyone follows the rules and funds keep coming in.

In the Philippines, the use of these kinds of tools is still limited and spread out across the country. Metro Manila has started to connect its CCTV networks, but these efforts aren't always uniform across cities, aren't centralized, and can't analyze data in real time (RuaCorp, 2021; BusinessMirror, 2022). Traffic control and enforcement still rely on a lot of manual reporting and people on the ground. This slows things down, costs more, and leaves the system open to mistakes and corruption (Garcia et al., 2020; Reyes & Lim, 2019). Also, there isn't a central database for traffic violations, and many local government units (LGUs) work alone and don't share and connect enforcement data. This makes it very hard to coordinate and make sure that the law is followed consistently across the country (Torres et al., 2022; Dela Cruz & Santos, 2021).

Traffic violations are still a problem in places like Metro Manila that have a lot of people. Ignoring traffic signs, loading and unloading illegally, swerving, and driving recklessly are all common offenses. According to the Japan International Cooperation Agency (JICA, 2018), around PHP 3.5 billion is lost every day because of traffic-related problems, many of which are caused by people breaking traffic rules. Studies have also shown that poor traffic regulation and limited use of technology are major problems. For instance, RuaCorp (2021) talked about the problems with manual regulation and how these kinds of systems can be hacked or messed up by people. BusinessMirror (2022) also pointed out that widespread noncompliance is caused by a lack of standardized training and general awareness.

Traffic violations are common in Calabarzon, especially in Laguna. They have a big effect on road safety and city order. According to a study by Reyes and Lim (2019), the main reasons of traffic problems are careless drivers, passengers, and pedestrians who do things like crossing the center line, not paying attention to traffic signs, and going too fast. Even though CCTV setups and random spot checks have been used to try to keep an eye on violations, enforcement is still mostly reactive and inconsistent (Garcia et al., 2020). Dela Cruz and Santos (2021) also found that high-violation areas can't get help quickly because they don't have adaptive, data-driven traffic enforcement tools. These violations have mostly gone unnoticed because of the rise in the number of cars on local roads and the lack of improvements in traffic regulation (Torres et al., 2022).

The suggested system fills in these gaps by creating a web-based system that combines real-time records for keeping track of traffic violations. The system will have features to identify repeated violators, keep track of fees paid and unpaid, and monitor the violation hotspot using geo-spatial mapping. It will also give traffic officers who apprehend drivers access to full records of violations, including information on first-time, repeat, and future offenders. The system will also assign apprehension officers based on patterns of violations and how well officers do their jobs. This method makes the enforcement process more effective and based on data, which helps Laguna with its unique problems.

B. *Project Context*

Enforcement of traffic violations in Laguna is still a big problem because old, human methods are still used (Francia et al., 2016). Paper-based methods are still used by many cities and towns to keep track of violations, which causes mistakes, waste, and a lack of coordination between law enforcement agencies (Del Rosario, 2019). This disorganized method has made it harder for authorities to keep accurate records of violations, tell the difference between first-time and repeat offenders, and make sure that fines are collected correctly (Lim, 2022). As a result, few people follow traffic laws, and the method for making sure they are followed doesn't work very well.

There is a major problem with managing traffic because of this bad situation. Officers who are enforcing the law often can't make good choices without a central database or real-time access to records of violations (Manuel, 2021). The Laguna Traffic Enforcement Division says that in 2021, only 40% of complaints are properly recorded, and less than 30% of fines are collected.

During a gap analysis, the researcher found this problem: there isn't a single digital system in Laguna that makes it easier to keep track of, report, and handle traffic complaints. Enforcement is inefficient and can't come up with proactive plans because there aren't any real-time analytics, automatic reporting tools, or ways to keep track of past violations. Studies from the past, like those by Perez et al. (2020), Reyes and Manuel (2021), and Santos and Lim (2022), back up this finding. They stress how important digital platforms are to improve compliance and help with data-driven traffic enforcement.

Since there are more people using the roads and more violations, the standard manual systems can't keep up. Making a web-based tool is part of the project's plan to close the gap between finding traffic violations and making people pay for them. The platform will let people see records in real time, keep track of fines, and give officers based on performance and pattern of violations.

This study is important and comes at the right time because it directly addresses the rising need for smart governance and traffic management tools in local government units. The software that will be developed will not only help law enforcers make decisions, but it will also set up a centralized, open, and accountable system that works with new technology and meets the needs of the people.

C. Research Objectives

This study aims to develop a web-based analytics system with prescriptions for traffic violations management in local government unit.

Specifically, the study seeks to achieve the following objectives:

1. To design a system that enables apprehending officers to access violation records, including identification of first-time and repeat violators, by automatically setting penalties based on prior violations.
2. To develop a web-based platform that integrates real-time records for tracking traffic violations with the following features:
    1. Monitor Frequent Violation Codes
    2. Hourly Violation Counts by Place
    3. Monthly Count of Violations
    4. Paid and Unpaid Payments
3. To implement a geo-spatial mapping feature that visualizes traffic violation hotspots and trends, with filtering capabilities by time, year, month, and violation code.
4. To integrate and evaluate the accuracy of a Decision Tree V6, utilizing prescriptive analytics for assigning and scheduling apprehension officers based on violation trends and officer performance.
5. To evaluate Software Quality based on ISO 25010.
6. To evaluate the Acceptability of TODA drivers and STMO personnels using Technology Acceptance Model.
7. To determine if there are no significant difference in the result of acceptability of the system by TODA driver and STMO personnels.

D. Hypothesis

This study will be guided by the following null hypothesis:

H_0: There are no Significant differences between TODA Drivers and STMO officers' terms of perceived of usefulness, perceived ease of use, Attitude toward using, and Behavioral Intention to use.

E. Conceptual Framework

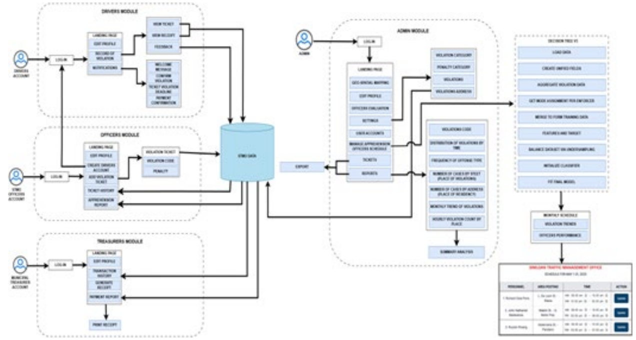

Fig. 1. E-TRAVIO Conceptual framework

Figure 1 shows that the study's conceptual framework is made up of four parts. The process starts when any of the four types of users—Administrator, Apprehending Officer, Driver (Violator), or Treasurer—logs in through their assigned module. After logging in, each user is taken to a landing page that is specific to their role and gives them access to tools and apps that are useful for their job.

The system gives administrators a lot of power and configuration options. The administrator can handle officer and user accounts, set up violation categories and penalties, check on officer performance based on feedback from drivers, and get to violation data in the central STMO database from the landing page. The Geo-Spatial Mapping feature also lets administrators see where and when traffic violations happen based on time, location, month, and violation code. There are filtering tools in this module to help with strategic rollout. A decision tree V6 is built into the system to automatically assign officers based on past violations, time of day, and the needs of each area. With these insights, managers can put officers in places with a lot of violations, making the deployment more efficient.

Officers who are apprehending violators use the system to directly report violations. After logging in, they can use the tools to print digital tickets, choose violation codes and penalties from a list, and share data about people who have been arrested. These entries are saved in the STMO database and can be used right away as needed. In cases where a violator does not yet have a registered account, officers can also build a driver profile in the system. This makes sure that each violation is properly linked to a user. This speeds up the process of keeping records and makes sure that no arrest is missed. The enforcers can also look at their past tickets.

Drivers can use the system to see what traffic violations they've committed by looking at the details of their tickets and the penalties they face by comparing their citation tickets and receipts. Each violation is immediately linked to the driver's profile, which makes it easy to keep track of records and manage them. The system also has a way for drivers to rate or comment on the performance of the apprehension officers who are apprehending violators. This helps with keeping track of performance and making improvements all the time. This feature makes things clearer, motivates people to follow the rules on time, and helps make the process of fixing violations faster and more accountable.

After violators look at their tickets and learn about their fines through the system, they pay their fines at the Municipal Treasury Office. The treasurer gets into the system and sees the violator's ticket and penalty information, which was entered and saved by the apprehending officers who caught them. The treasurer can see all relevant payment transactions, check the submitted receipts for accuracy, and have official receipts made automatically with all the necessary information already filled in. It is tied to the driver's profile in the STMO database and can be seen by the driver through their account once payment is confirmed. The treasurer's dashboard also has regular reports that list violations that have been paid and those that have not. This makes it easy to keep an eye on penalty collections and promotes financial transparency. This smooth process encourages responsibility, accuracy, and speed in managing money and enforcing traffic laws.

The last part of the system is all about reports and analytics. The supervisor can make summary reports using important information like the number of violations, the time periods, the violation codes, and the types of users. Anyone can save these reports and look at them somewhere else. They come with simple graphs and charts. This helps pick new policies, figure out how well the ones that are already in place are working, and spot patterns.

The system also uses prescriptive data to help the supervisor make plans. It makes a monthly plan for apprehension officers based on past data, such as areas with a lot of violations and how well officers did their jobs. The method places apprehending officers based on where the most violations happen and how well each officer does their job. This saves time and money, keeps people safe, and gets things done faster.

2. Review of Related Literature

A. *Traffic Management System*

Traffic Management Systems (TMS) let you keep an eye on people who break the rules of the road, record them, and punish them in different ways. With these systems' high-tech tools, you can keep an eye on things in real time and cut down on violations. A study by Zhang et al. (2020) found that TMS with traffic cams and analytics can quickly find and punish people who break common rules like speeding and running red lights. Khanna and Ghosh et al. (2019) also said that collecting data in real time is important for modern TMS because it lets people act faster on violations and make choices based on data. Wang et al. talked about how AI can help find traffic violations in 2021. They said that AI could do this by studying the rules and finding out where people are most likely to break the law.

TMS are also being used more and more to help with systems that enforce the law on their own. Zhang et al. (2022) say that real-time violation detection in TMS improves compliance by letting authorities know about violations faster and making fines work better. Patel and Gupta et al. (2021) also found that automatic ticketing systems built into TMS make it easier to keep track of things and make sure that fees are paid quickly and properly, without any mistakes. Smith et al. (2021) also said that using analytics in TMS helps officers find trends of violations. This lets them make rules that are clearer and work better.

With better AI and IoT, TMS can now handle problem data even better. Liu et al. (2022) discovered that systems powered by AI look at a lot of data to discover trends in the way drivers behave, which can help them guess when they will break the law again. A study by Kumar et al. (2020) also found that role-based access in traffic systems keeps private information about violations safe and makes officers more accountable for how they use the systems. Luo et al. (2020) also talked about how predictive analytics can be used to find ahead of time places where there are likely to be a lot of violations. This helps the traffic officers plan their work better.

TMS is better at stopping violations when everyone works together and gets active in the community. There was a lot of talk in 2020 about how important it is for different government agencies to work together to make TMS bigger so that it can be used to enforce traffic rules. This is especially true when legal, technical, and tactical parts are all put together. Li et al. (2021) also talked about the good things that can happen when people help build traffic systems. They said that getting feedback from the community helps make rules and ways of enforcing them that are clearer and work better. Ahmed et al. (2019) also looked at how cars and infrastructure can talk to each other and how this can be used to automatically report violations, which is useful at intersections where officers don't have much time to do this.

It is also very important to be able to grow and change when you use TMS to enforce traffic rules in smaller places. Zhang et al. (2022) came up with TMS designs that are different for each area and can be changed to fit their needs. This would give towns and cities time to slowly start using new tools for officer’s work. Tan et al. (2020) also showed that cloud-based TMS greatly lowers the cost of hardware and makes it easier to digitally handle violation data and fines. Kumar et al. (2021) also talked about how localized data analytics in TMS can help find trends of violations in a neighborhood. This makes it possible for officers to work faster and better. Lee et al. (2021) discovered that people are more likely to follow traffic rules on their own when they have a say in how the system works.

One interesting example of a Traffic Management System (TMS) made and used in the Philippines is the No Contact Apprehension Program (NCAP). The Metropolitan Manila Development Authority (MMDA) and some city governments, such as Valenzuela and Quezon City, started it. In this system, automated CCTV cameras and software that reads license plates are used to find traffic violations and give out tickets without any help from a person. An MMDA success report from 2021 says that the NCAP greatly raised the rate of compliance in places that were being watched. This was possible since the NCAP made it harder to pay people and didn't need traffic officers to be there.

There was a study in the Philippine Journal of Public Administration in 2021 by De Guzman and Estrella that looked at how well NCAP worked in Metro Manila. They found that it not only helped the government do its job better, but it also made it easy for people to pay online fines. Still, the program had issues with data protection and due process, as shown by the fact that the NCAP couldn't start for a short time in 2022 (Supreme Court of the Philippines, 2022). The system is still a big step forward, even with these issues. It shows that the Philippine government is trying to use a mix of technologies to improve complaint handling and digitalize traffic law enforcement.

B. Decision Tree

Decision tree algorithms are being used more and more in smart traffic control systems to find and predict people who will break the rules of the road. By splitting data into parts based on trait values, these algorithms give you a clear, rule-based way to decide what to do. Chopra et al. (2020) said that decision trees like ID3 and CART are easy to understand. Because of this, they can be used by officers when they need to be open. Also, Kumar and Desai et al. (2021) showed that decision tree models can correctly guess traffic violations by looking at where, when, and what kind of violations have happened in the past. Also, Lee et al. (2019) said that these models can help officers figure out how people act in ways that lead to a lot of violations.

If you want to know who will break the law, decision trees can sort and predict things that are likely to go wrong. A C4.5-based decision tree model was used by Patel et al. (2020) to find out what makes people do common traffic violations like speeding and running red lights. Ahmed et al. (2021) also found that decision trees that use traffic data that is specific to a place can correctly mark areas where violations are likely to happen. In their 2019 paper, Fernandez and Wong et al. also talked about how decision trees can help make more accurate predictions of the risk of violations by taking into account many things, like the type of car, the amount of traffic, and the weather.

Not only are decision tree algorithms good at guessing, they have also helped keep track of how resources are used. This idea from Santos et al. (2022) says that officers should use decision trees to help them figure out where to put themselves based on areas with a lot of violations and a history of giving tickets. They also said that choice tree results help managers better plan traffic checks so that they go to places and times where there is a high chance of violations. Narayan et al. (2021) did another study that showed it is easier to find "hotspots" when you use both decision trees and satellite maps together. This helps offices directly make better plans for their strategies.

Decision trees have also been used to make it easier to handle cases of violations and cut down on unnecessary steps in the way law enforcement works. Khan et al. (2021) created a system that uses decision trees to sort traffic violations into two groups: first-time and repeat offenses. This helps traffic officers focus on the cases that need their instant attention. In the same way, Bautista et al. (2020) used decision tree logic to automatically group violations into groups for digital ticket handling. This cut down on the time people had to wait for paperwork. Also, Singh and Patel et al. (2022) found that these models make it easier to deal with violations because they offer the right fines or measures based on how bad the violation was and how it happened before.

Though they have some uses, decision tree models in traffic systems can get too good at what they do and are easily fooled by too much noise in the data. Cheng et al. (2021) said that trimming methods and group methods like Random Forest are often used to add more trust to decision trees in real-life traffic situations. Rahman et al. (2022) also talked about how important it is to keep feeding models new data so that they can keep working in traffic conditions that change all the time. Last but not least, Tanaka and Yoon et al. (2021) said that decision tree models should be added to bigger traffic control systems, such as real-time databases and officers' dashboards, to help people make the best choices possible.

3. Review of Related Literature

A. Research Design

This This study will employ a developmental and descriptive research design to create, implement, and evaluate a web-based application tailored for the Siniloan Traffic Management Office. The developmental aspect focuses on the systematic design, development, and refinement of the application, ensuring that it integrates features such as interactive dashboards, violation tracking, and historical record accessibility to meet the needs of traffic officers and administrators (Anderson & Shattuck, 2019). The descriptive part looks at how well the system works to improve traffic violation management by gathering and studying information on how engaged users are, how easy the system is to use, and what officers have to say (Creswell & Creswell, 2020). When these two methods are used together, the study makes sure that the app is not only well-designed but also good at fixing issues that come up when traffic rules are being enforced.

B. Population of the Study

The study was conducted in the Province of Laguna, specifically in the Municipality of Siniloan, which served as the target user area. The people being studied are 13 people who work for Siniloan Traffic Management, one person who works for Siniloan Traffic Management, one person who works for the city treasury, and 677 TODA drivers in Siniloan, Laguna. These people are directly involved in enforcing traffic laws, giving tickets for violations, and handling the administrative tasks needed to keep track of penalties and make sure they are followed. The population is made up of officers and staff with different jobs and levels of experience who use the system or gain from it. The outlined population makes sure that the study's goals and the app's target users are in line with each other.

C. Sampling Design

The study uses a mixed sampling method to get a complete and accurate sample. Purposive sampling is used for key people involved in enforcement and processing of fines, and stratified sampling is used for TODA drivers.

The people who work in traffic control, the STMO officer, and the municipal treasurer all use purposeful sampling. People are chosen for this non-probability sampling method based on their expertise, job, and how they relate to the study's goals

(Etikan & Bala, 2019). These people are very important because they directly enforce and keep an eye on traffic rules, so their opinions are very important. Pálinkas et al. (2023) say that purposeful sampling is a common way to get detailed information from people who have a lot of knowledge.

To make sure that different driving experiences are shown, TODA drivers in Siniloan, Laguna are chosen using stratified sampling. Stratified sampling is a chance-based method that divides a community into smaller groups called strata and picks people at random from each stratum (Lohr, 2019; Taherdoost, 2020).

Stratified sampling was used in this study to make sure that all 677 TODA users were fairly represented. The people in the community were put into different groups based on their membership, and samples were chosen at random from each group. Using Slovin's method, Table 1 shows that a total sample size of 246 respondents was found and sent out in the right way.

Table 1
Stratified sampling distribution of TODA drivers

Toda Drivers	Percentage	Sample Size
3WHEELS	1.61%	4
7ELEVEN	3.84%	9
BBTODA	3.39%	8
BLSTODA	1.18%	3
BUTODA	13.44%	33
HATODA	4.43%	11
KAPTODA	10.76%	26
KATODA	5.88%	14
LIPTODA	2.79%	7
LSPU EXPRESS	8.12%	20
MTODA	3.39%	8
MSTODA	6.35%	16
PATODA	4.87%	12
RAMTODA	2.65%	7
ROTA	9.01%	22
SATODA	6.35%	16
SESTODA	2.65%	7
SETODA	5.01%	12
SFBTODA	1.47%	4
SHTODA	2.65%	7
Total	**100%**	**246**

D. Data Collection Instrument

1) Interviews

At the Siniloan Traffic Management Office, the researcher talked to municipal treasurers and traffic management workers. The goal of these talks was to find problems that people are having with giving out tickets, keeping track of violations, and getting to old records. The conversations gave us information that helped us design the system's features, taking into account both user needs and inefficient ways of doing things.

2) Questionnaire

Once the system was completed, surveys were distributed to a targeted group of respondents—specifically, staff from the Siniloan Traffic Management Office (STMO), the management officer, the municipal treasurer, and local drivers. These were provided in both electronic and paper formats to ensure inclusivity and accessibility.

Two well-established evaluation models were used: the Technology Acceptance Model (TAM) and the ISO/IEC 25010 software quality model. The TAM framework, originally proposed by Davis (1989), has been widely used to assess user acceptance of new technologies by evaluating perceived usefulness, perceived ease of use, attitude toward use, and behavioral intention to use. In this study, the TAM-based questionnaire aimed to determine users' perceptions of the traffic violation management system in terms of its usefulness in completing daily tasks, ease of navigation, overall user satisfaction, and likelihood of continued use or recommendation. Several studies (e.g., Venkatesh & Davis, 2000; Legris, Ingham, & Collerette, 2003) support the robustness of TAM in evaluating user interaction with technology in both public and private sector systems.

The ISO/IEC 25010 quality model, published by the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC), provides a comprehensive framework for evaluating the technical quality of software systems. This model outlines eight quality characteristics, including functionality, reliability, usability, performance efficiency, maintainability, portability, security, and compatibility (ISO/IEC 25010:2011). In this study, the focus was on assessing the system's functionality (completeness, correctness, and appropriateness), reliability (maturity, fault tolerance, availability, and recoverability), and other core attributes. The adoption of ISO/IEC 25010 is supported by various case studies (Gresse von Wangenheim et al., 2010; Al-Qutaish, 2010) that demonstrate its effectiveness in guiding software evaluation in diverse application contexts.

The Usability part of the evaluation looked at how easy and clear the system was for the people who were supposed to use it. It looked at things like how easy it was to understand what the system was for, how quickly and easily people could learn how to use it, how easy it was to control and operate while in use, and how well it looked and worked for people with different abilities. As part of the Performance Efficiency dimension, we looked at how quickly the system replied to tasks, how well it used its resources (resource utilization), and how many people or tasks it could handle at once. Finally, the Portability aspect was used to see how flexible the system was when it was moved to different places or devices, making sure it could be used with a variety of technology.

A five-point Likert scale was used to rate each item in the ISO 25010 questionnaire. Five was the highest amount of satisfaction and one was the lowest. With the help of a professional statistician, the answers were looked at statistically to find out what worked well and what could be done better with the system. This thorough testing process gave a full picture of the system's quality from both a technical and a user-centered point of view.

Table 2
ISO 25010 Likert scale

Scale	Range	Description Rating
5	4.20-5.00	Strongly Agree
4	3.40-4.19	Agree
3	2.60-3.39	Neutral
2	1.80-2.59	Disagree
1	1.0-1.79	Strongly Disagree

The Technology Acceptance Model (TAM) Likert scale is used to measure the acceptability of the system among users. As shown in Table 3, a rating of 5 indicates that the system is highly acceptable, while a rating of 4 reflects moderate acceptability. A rating of 3 shows that users are somewhat accepting of the system. A rating of 2 suggests slight acceptability, and a rating of 1 means the system is not acceptable at all.

Table 3
Technology acceptance model Likert scale

SCALE	RANGE	DESCRIPTION RATING
5	4.20-5.00	Highly Acceptable
4	3.40-4.19	Acceptable
3	2.60-3.39	Moderately Acceptable
2	1.80-2.59	Unacceptable
1	1.0-1.79	Highly Unacceptable

E. Statistical Treatment

Both descriptive and inferential statistics were utilized to summarize, analyze, and interpret the survey data collected in this study. As shown in Table 4, Descriptive statistics, specifically the Average Weighted Mean (AWM), were used to evaluate the software quality of E-TRAVIO based on ISO 25010 standards. This tool provided meaningful summaries of how the system was perceived by IT experts in terms of Functionality, Reliability, Portability, Usability, and Performance. The same statistical tool was applied to assess the acceptability of the system among TODA drivers and STMO personnel using the Technology Acceptance Model (TAM) framework.

To determine whether there was a significant difference in the level of system acceptability between TODA drivers and STMO personnel, the researcher used the Mann-Whitney U Test, a non-parametric inferential statistical tool appropriate for comparing two independent groups. This allowed for a robust analysis even when the assumptions of normal distribution were not guaranteed.

Using both descriptive and inferential tools together made it possible to get a full picture of user feedback and differences in how they saw things, which made sure that the study results were reliable and in-depth (Creswell, 2019).

4. Result and Discussion

For clarity and organization, the researcher refers back to the specific questions set out in Section 1.

A. To Design a System that Enables Apprehending Officers to Access Violation Records, Including the Ability to Identify First-Time and Repeat Violators, by Automatically Setting Penalties Based on Prior Violations

The main purpose of this objective is to streamline and enhance the enforcement of regulations by equipping apprehending officers with a system that offers immediate access to an individual's violation history. By enabling officers to distinguish between first-time and repeat offenders, the system ensures that penalties are assigned more accurately and fairly, based on the violator's prior record. This automation not only promotes consistency in penalty enforcement but also reduces human error and administrative workload. Ultimately, the objective aims to support more efficient decision-making, deter repeat offenses, and uphold a more just and effective regulatory framework.

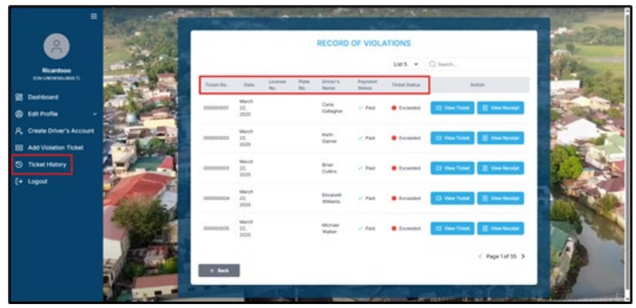

Fig. 2. E-TRAVIO record of violations

Figure 2 illustrates the “Record of Violations” feature within the system interface, which provides apprehending officers with streamlined access to detailed records of traffic violations. This feature lists critical information such as ticket number, date, license and plate numbers, driver’s name, payment status, and whether the ticket status has exceeded the allowed timeframe.

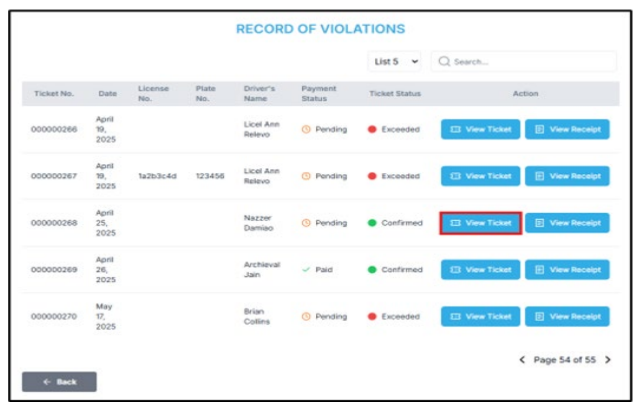

Fig. 3. View violation ticket feature

Figure 3 demonstrates the detailed functionality of the violation management system, specifically highlighting how officers can access individual citation tickets through the “View

Table 4
Statistical tools and formulas used for data analysis

Objectives	Statistical Tools	Formula
Result of Software Quality evaluation based on ISO 25010. Evaluate the Acceptability of TODA drivers and STMO personnels using Technology Acceptance Model.	AVERAGE WEIGHTED MEAN	$AWM = \frac{\sum(X \times W)}{\sum W}$
To determine if there are significant difference in the result of acceptability of the system by TODA driver and STMO personnels.	MANN WHITNEY U TEST	$u_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1$ $u_2 = n_1 n_2 + \frac{n_2(n_2+1)}{2} - R_2$

Ticket” feature. Officers can click the "View Ticket" button to open a detailed citation.

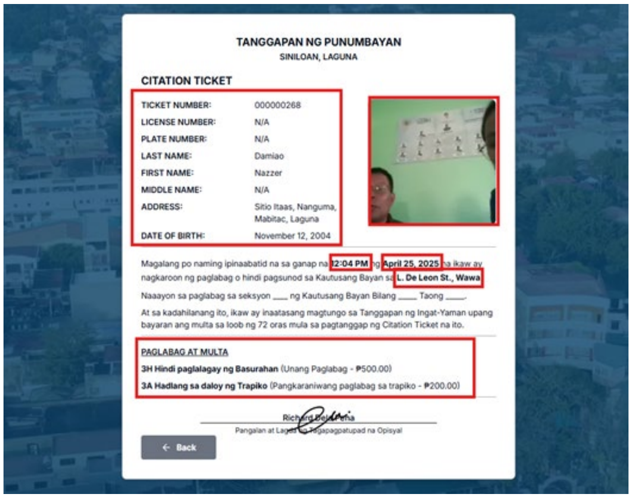

Fig. 4. Citation ticket

As shown in Figure 4, the ticket includes comprehensive information such as the violator's full name, address, date of birth, violation date and time, location, specific infractions committed, and corresponding penalties. Additionally, it features a visual record and a space for officer verification. This feature improves transparency and accountability by enabling accurate documentation and retrieval of violation records, which supports fair enforcement and efficient processing of penalties.

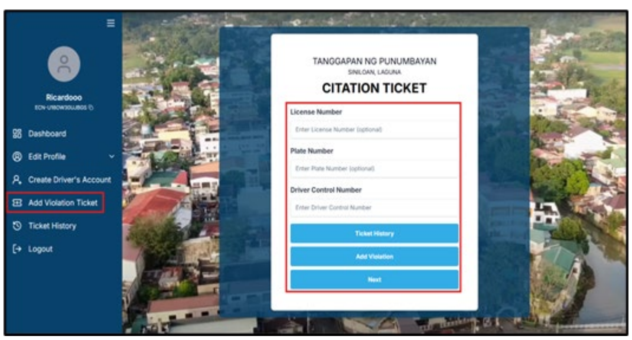

Fig. 5. Add violation ticket

Figure 5 presents the "Add Violation Ticket" interface, a feature designed to streamline the process of issuing citation tickets by enforcement officers. This form allows officers to input key information such as the driver’s license number, vehicle plate number, and a unique driver control number, with the first two fields marked as optional to accommodate situations where such details may not be immediately available. Below the input fields are quick-access buttons for viewing ticket history, adding violation details, or proceeding to the next step.

The main purpose of this feature is to simplify and digitize the ticketing process, ensuring that violations are recorded accurately and efficiently even in the absence of complete driver or vehicle data. By enabling easy data entry and seamless navigation, the system improves the speed and reliability of violation documentation, which ultimately supports more effective enforcement and record-keeping.

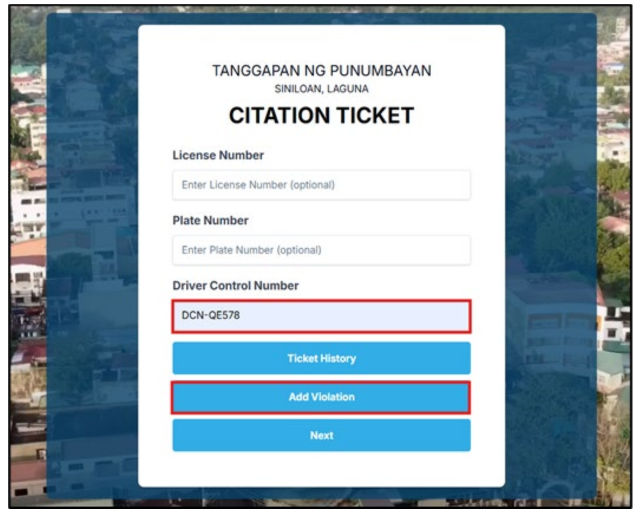

Fig. 6. Citation ticket interface showing driver control number input and violation entry options

To add a violation ticket in the system shown in the Figure 6 the apprehending officers must first input the Driver Control Number (DCN) of the violators. This unique code is assigned to each driver account when it's created, and it is required for identifying the correct individual before proceeding with any actions like viewing ticket history or adding violations.

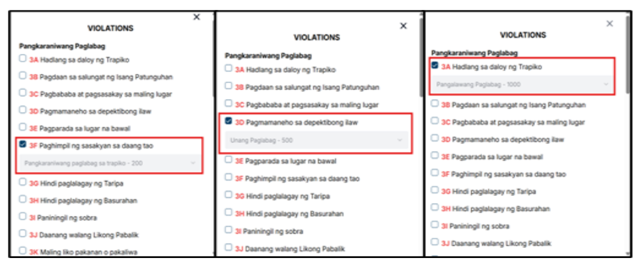

Fig. 7. Automatic penalty identification based on violation history

After clicking the "Add Violation" button, a list of common traffic violations will appear, as shown in the Figure 7.

The user can then select the specific offense committed by the driver. Once a violation is selected, the system automatically assigns the corresponding penalty amount based on the driver’s violation history. For instance, first-time violators are fined ₱200, second-time violators are charged ₱500, and third-time or repeat violators are penalized with ₱1000. This automated feature ensures accuracy and fairness by increasing the penalty for repeat offenders and streamlining the entire ticketing process.

The system is designed to assist apprehending officers by providing immediate access to a driver's violation history, enabling accurate identification of first-time and repeat offenders. Through a user-friendly interface, officers can efficiently issue violation tickets, view detailed citation records, and apply penalties that are automatically adjusted based on prior infractions. Features such as the “Record of Violations,” “View Ticket,” and “Add Violation Ticket” streamline the enforcement process, reduce human error, and enhance transparency and accountability. Ultimately, the system promotes fair, consistent, and efficient regulation enforcement while minimizing administrative workload.

B. To Develop a Web-Based Platform that Integrates Real-Time Records for Tracking Traffic Violations with the Following Features

1) Monitor frequent violation codes

The main purpose of developing a web-based platform that integrates real-time records for tracking traffic violations—specifically featuring the ability to monitor frequent violation codes—is to provide traffic authorities with immediate insights into the most commonly committed offenses. This functionality allows enforcement agencies to identify patterns in driver behavior, detect high-risk violations, and prioritize interventions or awareness campaigns accordingly. By continuously updating and displaying data on frequent violations, the system supports more targeted enforcement, informed decision-making, and the development of proactive strategies to improve road safety and compliance.

This report is only accessible through the Administrator account. As shown in the Figure 8, it includes features that display various analytical reports designed to assist the administrator in monitoring and evaluating traffic violation trends.

Fig. 8. Top 5 violations by violation code report

When you click the "Report of Top 5 Violations by Violation Code", it will display the total number of recorded violations categorized by each specific violation code. This report allows the administrator to clearly see which types of violations are most common, helping to identify patterns and areas that may require increased enforcement or public awareness. The visual representation of data makes it easier to interpret trends and prioritize actions based on the frequency of each violation type.

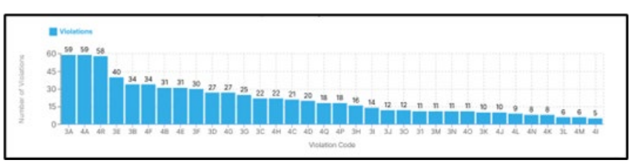

Fig. 9. Number of violations by violation code report

2) Hourly Violation Counts by Place

The purpose of developing a web-based platform with the Hourly Violation Counts by Place feature is to enable traffic authorities to monitor when and where violations occur most frequently throughout the day. By tracking the volume of violations by location on an hourly basis, this feature provides valuable insights into peak times and high-risk areas for traffic offenses. This real-time data supports better planning and deployment of enforcement personnel, enhances situational awareness, and helps in designing targeted traffic management strategies. Ultimately, it contributes to improving road safety, reducing congestion, and ensuring more efficient and proactive enforcement operations.

Fig. 10. Hourly violations counts by place

Figure 10 shows the "Hourly Violation Count by Place" report, a feature available in the admin dashboard. This chart visually represents the number of traffic violations committed at specific locations, broken down by the hour of the day. Different streets are tracked and color-coded for clarity.

3) Monthly Counts of Violations

The Monthly Count of Violations feature is designed to provide administrators with a clear and organized view of how many traffic violations occur each month. Its main purpose is to help track trends over time, identify months with spikes or drops in violations, and assess the effectiveness of enforcement strategies or public awareness campaigns. By analyzing this data, administrators can make informed decisions about when to increase patrols, launch educational efforts, or review traffic policies. This feature supports long-term planning and enhances the overall efficiency of traffic management by offering a broader perspective on violation patterns throughout the year.

Fig. 11. Monthly count of violations

This feature provides a visual summary of the total number of traffic violations recorded each month. As shown in the Figure 11, there is a noticeable decline in violations from March 2025 to June 2025, indicating either improved compliance, effective enforcement, or seasonal patterns in traffic behavior.

This data is especially useful for administrators as it allows them to monitor trends over time, evaluate the impact of enforcement strategies or public safety campaigns, and identify periods requiring additional attention or intervention. By understanding monthly fluctuations, decision-makers can plan more targeted and data-driven traffic management and enforcement policies.

4) Paid and Unpaid Payments

Paid and Unpaid Payments feature allows administrators and Municipal Treasurers to efficiently monitor the status of traffic violation fines by providing a clear and real-time breakdown of which violations have been paid and which remain unpaid. This feature enhances accountability by helping identify drivers with outstanding penalties and supports timely follow-up or enforcement actions. It also enables the analysis of payment trends, improves the effectiveness of revenue collection, and ensures that violators are held responsible for their infractions. Overall, it contributes to a more transparent, organized, and responsive traffic enforcement system.

The highlighted section in the image shows a line graph comparing Paid and Unpaid Violators over several months, under the report titled "Top Violations by Code." This visual representation distinguishes between violators who have settled their fines (in blue) and those who have not (in red), tracked across the months of March to June.

Fig. 12. Monthly number of paid and unpaid violators

From the Figure 12, it is clear that in March, the number of unpaid violators was significantly higher compared to paid ones, but there was a consistent decline in unpaid violations in the following months, while the number of paid violators remained stable or increased slightly. This trend may indicate improved compliance, successful follow-ups, or more effective enforcement and payment processing strategies.

This report helps administrators assess payment behavior, identify patterns in compliance, and take appropriate actions to improve collection and accountability.

This web-based platform is designed to help traffic authorities and administrators efficiently track, analyze, and manage traffic violations through real-time data and visual reports. Key features include monitoring the Top 5 Frequent Violation Codes, Hourly Violation Counts by Place, Monthly Counts of Violations, and Paid vs. Unpaid Payments. These tools provide valuable insights such as identifying common violations, pinpointing peak hours and high-risk areas, observing monthly trends, and tracking fine payment compliance. Accessible only to administrators (and in some cases, Municipal Treasurers), the system enhances decision-making, enforcement planning, and public safety initiatives. Through clear visualizations and automated reporting, it promotes accurate monitoring, effective policy implementation, and improved transparency and accountability in traffic management.

C. To Implement a Geo-Spatial Mapping Feature that Visualizes Traffic Violation Hotspots and Trends, with Filtering Capabilities by Time, Location, Month, and Violation Code

The purpose of implementing a geo-spatial mapping feature is to visually identify and analyze traffic violation hotspots and emerging trends across different areas. By allowing filtering by time, location, month, and violation code, this feature enables traffic authorities and administrators to gain precise insights into where and when violations are most frequent. It supports data-driven decision-making by making it easier to allocate enforcement resources effectively, plan strategic interventions, and implement targeted traffic safety measures. Ultimately, this feature enhances situational awareness, improves public safety, and promotes smarter, location-based traffic management.

Fig. 13. Distribution of violations in Siniloan, Laguna

Figure 13 showcases the interactive map interface of the developed system. It has markers indicate locations where violations occurred, giving users an intuitive spatial understanding of violation hotspots. This central visualization tool aids traffic authorities and administrators in analyzing and managing traffic violations more effectively by combining location-based insights with violation statistics.

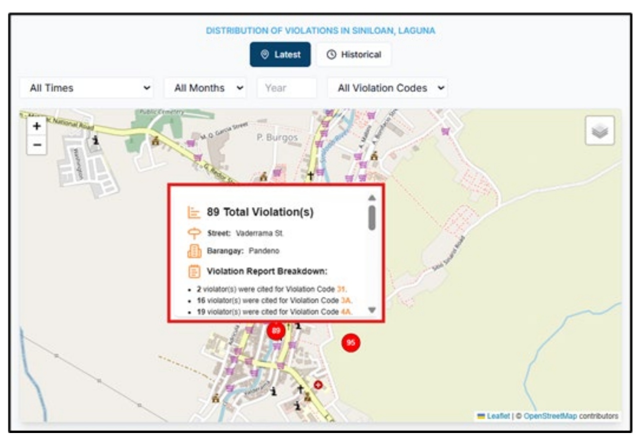

Fig. 14. Violations breakdown

As shown in the Figure 14, the feature is triggered when a user clicks on a red marker indicating a location where traffic violations occurred. In this case, the marker represents 89 total violations recorded along Vaderrama Street in Barangay Pandeno.

The popup window provides a detailed breakdown of the violations in that area. It lists each violation code and the corresponding number of violators, offering a clear summary of the most common offenses. For instance, 2 violators were cited for Violation Code 31, 16 for Code 3A, and 19 for Code 4A. This breakdown helps in identifying the nature and frequency of violations at specific locations.

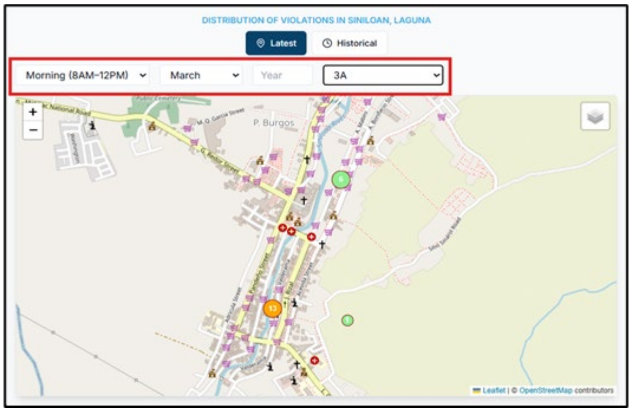

Fig. 15. Distribution of violations in Siniloan, Laguna with filtering

The highlighted section in the Figure 15 showcases the filtering options available in the Geo-Mapping interface for the distribution of violations in Siniloan, Laguna. This feature provides users with the ability to refine the data displayed on the map based on specific criteria. Users can filter violations by time of day to observe patterns during particular hours. Additionally, the interface allows filtering by month and year, enabling users to focus on violations that occurred within a selected timeframe. Furthermore, the system includes a filter for violation codes, allowing users to isolate specific types of violations.

The geo-spatial mapping feature of the developed system enables the visualization of traffic violation hotspots and trends in Siniloan, Laguna, with interactive filtering options. It allows users to filter data by time of day, location, month, year, and violation code, providing a detailed and dynamic view of where and when violations occur most frequently. This supports data-driven decision-making for traffic authorities by aiding in the strategic allocation of resources and the implementation of targeted safety measures. The interface uses markers to represent violation locations, and clicking on these reveals a breakdown of specific violations at each site. Figures 16 to 18 illustrate how the system provides both spatial and statistical insights, enhancing situational awareness and improving traffic management and public safety.

D. To Integrate and Evaluate the Accuracy of a Decision Tree V6 for Assigning and Scheduling Apprehension Officers Based on Violation Trends and Officer Performance

Figure 16 shows how the monthly schedule generation tool for STMO staff was put into use. This feature shows how prescriptive analytics can be used because it makes officer deployment schedules based on past data on traffic violations and individual success metrics. The system suggests the best areas for each enforcer to work by using known violation hotspots and trends.

Fig. 16. Monthly STMO Personnels schedule

This part comes with the Decision Tree V6 model already set up. It learned from past records of tickets, officers' deployment logs, and trends in spatial violations. It figures out where violations are most likely to happen and puts people in those places to make sure that punishments are as thorough and effective as possible. Based on data, this method makes sure that places with a lot of violations get the most attention and that law enforcement resources are spread out in the right way.

Adding prescriptive analytics not only makes planning and working decisions better, but it also makes things more fair, clear, and effective. It shows how machine learning can be used in real life to improve government by letting local governments move from reactive regulation to proactive, smart scheduling based on real-world data insights.

Table 5
Decision tree hyperparameters selected via grid Search CV

Parameters	Value
Max_depth	5
Max_features	sqrt
Max_leaf_nodes	None
Min_samples_leaf	2
Min_samples_split	2

Table 5 shows the best hyperparameters that GridSearchCV chose for the Decision Tree classifier. This shows the best way to set it up to make accurate results that can be used in other situations. The min_samples_split parameter is set to 2, which means that each internal node must have at least two samples that can be split further. This lets the tree get big enough to see detailed trends in the data. Also, min_samples_leaf is set to 2, which makes sure that each leaf node has at least two samples. This helps make decisions smoother and stops overfitting by keeping the model from fitting noise in the training data. If you set the max_leaf_nodes setting to None, the tree can have as many leaf nodes as it wants. This lets you build complex structures as needed while still following other rules. The max_features parameter is set to sqrt, which means that the algorithm looks at the square root of the total number of features at each split. This is a popular way to help reduce variance and make models more stable by limiting the number of features that are looked at at each split. Finally, the tree's depth is set to 5 (max_depth = 5). This limits the model's complexity, keeping it from getting too deep. This keeps it from overfitting and helps it work better with data it hasn't seen before.

This set of hyperparameters shows a reasonable way of dealing with model complexity. It trades off depth and feature consideration to make a model that can find important patterns in the data without fitting it too well. It is known that limiting max_depth and setting minimum samples per split and leaf are good ways to make decision trees more reliable and good at making predictions (Kotsiantis et al., 2021; Zhang & Chen, 2022). Moreover, using the square root of features at each split is a standard practice in classification trees that reduces correlation among trees in ensemble methods and usually improves generalization (Li et al., 2023). Overall, the hyperparameters that were chosen are in line with current best practices for tuning decision trees. They strike a good balance between freedom and control to get the best results (Wang et al., 2021).

Table 6
Classification report of decision tree

	Precision	Recall	F1	Support
C5 Road - P. Burgos	0.44	0.80	0.57	5
E. Castro St. - Pandeno	0.71	1.00	0.83	5
G. Redor St. - Pandeno	1.00	0.60	0.75	5
G. Redor St. - Siniloan Market	1.00	0.60	0.75	5
Q. Dela Rosa St. - Pandeno	0.67	0.40	0.50	5

The Decision Tree model's classification report shows mixed but hopeful results in five street locations, even though the dataset is small. Table 6 shows that out of all the classes, E. Castro St. - Pandeno did the best, with an accuracy score of 0.71, a recall score of 1, and an F1 score of 0.83. This means that the model correctly found all the important cases from this area while reducing the number of wrong predictions. C5 Road: P. Burgos found a high recall (0.80) but a lower accuracy (0.44), which means that the model correctly identified most true cases but also a few false positives. The model's predictions for the G. Redor St. - Pandeno and G. Redor St. - Siniloan Market were very accurate (1.00), but not all actual cases were found (0.60). This means that while all predictions were right, not all actual cases were found. With an F1 score of 0.50 and a recall of 0.40, Q. Dela Rosa St. - Pandeno had the worst result.

The Decision Tree model was able to get pretty good precision and recall in a number of places, even though the dataset was small (only five examples per class). Recent research has shown that Decision Trees can work well with small datasets, especially when the traits make it easy to tell the difference between classes (Zhou et al., 2021). Decision trees are non-parametric, which means they don't make assumptions about how the data is distributed. This means they can work well with small sample numbers and complicated decision boundaries without needing a lot of training data (Tan, Steinbach, & Kumar, 2019). They also give results that are easy to understand and can find local trends in small datasets (Wang et al., 2020). Even though performance varies between classes, the results show that Decision Trees are still a good and easy to understand choice for sorting jobs, even when there isn't a lot of data.

Table 7
Overall metrics of decision tree

Metrics	Value
Accuracy	0.68
Macro Avg	0.77 (precision), 0.68 (recall), 0.68 (f1-score)
Weighted AVG	0.77 (precision), 0.68 (recall), 0.68 (f1-score)

Table 7 shows that the Decision Tree model did about average, with an accuracy of 0.68, a macro average of 0.77 (precision), 0.68 (recall), and 0.68 (F1-score), and the weighted average having the same values. Based on these results, it looks like the model properly classified 68% of the cases and kept its accuracy across all classes.

The macro average treats all classes the same, no matter how much support they have, and the relatively high accuracy (0.77) means that the model did a good job of avoiding false positives in general. However, the recall (0.68) and F1-score (0.68) show that there is room for improvement in finding all important instances and finding a better balance between recall and precision. The fact that macro and weighted averages are in the same place further suggests that the spread of classes was pretty even or that the model did a good job of dealing with the class imbalance.

E. To Evaluate the Result of Software Quality Evaluation Based on the ISO 25010

The assessment focused on five core quality characteristics based on the ISO 25010 software quality standards—Functionality, Reliability, Usability, Portability, and Performance—reflecting a high level of overall system quality. As shown in Table 8, the evaluation results based on the ISO 25010 quality model indicate that the system achieved the highest ratings in both Functionality and Usability. These ratings suggest that the system effectively delivers the required features and offers a user-friendly experience. High functionality implies that the software meets specified tasks completely, correctly, and appropriately. According to ISO/IEC 25010:2020, these characteristics are critical in determining whether the system performs as intended within its operational context (ISO/IEC, 2020). Likewise, the strong usability rating reflects ease of use, interface clarity, and overall user satisfaction. Santos and Dias (2021) emphasized that systems with high usability not only improve user efficiency but also reduce training time and increase adoption rates—especially when interface aesthetics and accessibility are prioritized, both of which were rated highly in this evaluation.

In contrast, the lowest ratings were observed in Reliability and Portability, which still fall within an acceptable range but highlight relative areas for improvement. The lower score in Reliability, particularly influenced by fault tolerance, suggests that the system may have limited resilience in handling unexpected issues or failures. As Zhang et al. (2020) highlight, fault tolerance is essential for systems operating in dynamic or mission-critical environments, and enhancing this capability ensures continued service availability. Meanwhile, Portability, evaluated primarily through adaptability, also received a modest rating. This implies the system may not be as flexible or efficient when transferred to different platforms or environments. Lee and Kim (2022) argue that as organizations increasingly rely on diverse deployment infrastructures, including cloud and mobile platforms, improving software adaptability has become a strategic priority.

In summary, the system excels in being both functional and user-friendly, which is essential for meeting user expectations and ensuring productivity. However, enhancements in reliability and portability would further improve the system's robustness and deployment flexibility, aligning it more closely with the broader goals of software quality under ISO 25010.

Table 8
Total evaluation results IT experts in ISO 25010

No.	Questions	WM	Interpretation
A.	**Functionality**		
	Functionality Completeness	4.8	Functional
	Functionality Correctness	4.4	Functional
	Functionality Appropriateness	4.2	Functional
		4.5	Functional
B.	**Reliability**		
	Maturity	4.4	Reliable
	Availability	4.3	Reliable
	Fault Tolerance	4.2	Reliable
	Recoverability	4.3	Reliable
		4.3	Reliable
C.	**Portability**		
	Adaptability	4.3	Portable
D.	**Usability**		
	Recognizability	4.3	Usable
	Learnability	4.0	Slightly Usable
	Operability	4.5	Usable
	User Interface Aesthetics	4.7	Usable
	Accessibility	4.5	Usable
		4.5	Usable
E.	**Performance**		
	Time Behavior	4.4	Excellent Performance
	Resource Utilization	4.3	Excellent Performance
	Capacity	4.5	Excellent Performance
		4.4	Excellent Performance
Overall Weighted Mean:		**4.4**	**Excellent Performance**

F. Evaluate the Acceptability of TODA Drivers and STMO Personnels using Technology Acceptance Model

The evaluation results using the Technology Acceptance Model (TAM) framework, as summarized in Table 9, show a consistently high level of system acceptability from both TODA drivers and STMO personnel. All four core parameters—Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention to Use—received scores ranging from 4.5 to 4.7, falling within the "Highly Acceptable" category. Both groups rated Perceived Usefulness equally at 4.7, indicating a shared belief that the system enhances their task performance and productivity. Perceived Ease of Use scored slightly higher among STMO personnel (4.6) compared to TODA drivers (4.5), suggesting that while both groups find the system user-friendly, STMO personnel may have had slightly fewer difficulties during initial interaction. For Attitude Toward Using, TODA drivers scored marginally higher (4.7) than STMO personnel (4.6), reflecting a very positive reception among front-line users. Lastly, both groups rated Behavioral Intention to Use equally at 4.6, showing a strong commitment to continued system usage. Overall, the findings reflect widespread approval and readiness for adoption across user roles, validating the system's design, functionality, and relevance to their daily operations.

G. To Determine if there are Significant Difference in the Result of Acceptability of the System by TODA Driver and STMO Personnels

The Table 10 shows the result for Questions, analyzed using the Independent-Samples Mann-Whitney U Test, yields a significance value of .417, which is greater than the threshold of .05. This leads to the decision to retain the null hypothesis, meaning there is no statistically significant difference in responses to Q15 across the different groups of STMO personnel and TODA drivers. This suggests a shared perception or experience regarding the content of Q15, which may pertain to an aspect of technology acceptance such as trust, usability, or recommendation. The absence of significant difference reinforces the idea that the technology is being perceived similarly regardless of the user's role.

5. Summary, Conclusion and Recommendation

A. Summary

The system gives apprehending officers direct access to violation records, helping them distinguish between first-time and repeat violators. Penalties are assigned automatically based on prior offenses, ensuring consistency in enforcement, reducing manual workload, and minimizing errors. Key features include a centralized interface that shows ticket numbers, dates, driver and vehicle information, payment status, and ticket validity timelines. Officers can also open detailed citations that show violations committed, penalties imposed, and officer verification fields. The ticketing process is

Table 9
Summary of evaluation results using the TAM Framework with TODA Drivers and STMO Personnel

Parameter	TODA Drivers	STMO Personnels	Verbal Interpretation
Perceived of Usefulness	4.7	4.7	Highly Acceptable
Perceived Ease of Use	4.5	4.6	Highly Acceptable
Attitude Toward Using	4.7	4.6	Highly Acceptable
Behavioral Intention to Use	4.6	4.6	Highly Acceptable

Table 10
Hypothesis test summary

Null Hypothesis	Test	Sig.	Decision
The distribution of Questions is the same across categories of Groups.	Independent-Samples Mann-Whitney U Test	.417	Retain null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

streamlined through an input form that works even when complete data isn't immediately available. A unique Driver Control Number (DCN) is required to issue or view tickets, ensuring accurate and traceable recordkeeping.

The web-based platform offers real-time tracking and analytics tools for administrators. It can identify the most frequent violation codes, detect trends in hourly and monthly violation counts, and monitor payment status (paid vs. unpaid violations). These features help administrators recognize problem areas, improve planning for enforcement campaigns, and make informed decisions about policy and personnel deployment. The data insights are available only to admin-level accounts or authorized municipal treasurers, helping maintain data security while supporting accountability and efficient traffic management.

The system includes an interactive geo-spatial mapping feature that shows traffic violation hotspots across different locations. It allows filtering by time, place, month, year, and violation code. This helps authorities see when and where violations happen most frequently. Clicking on a map marker reveals a summary of violations at that spot, including the most common offenses. This visual and statistical integration supports better deployment of traffic enforcers and improves public safety through location-based strategies.

A Decision Tree V6 model was added to help schedule STMO personnel based on past traffic data and officer performance. The model analyzed ticket history and hotspot locations to recommend deployment areas. It was optimized using GridSearchCV, which selected parameters like max depth (5) and minimum sample split (2) to balance model accuracy and generalization. The model showed strong results in certain locations—for example, E. Castro St. had perfect recall (1.00) and an F1 score of 0.83. Overall, the model reached 68% accuracy and 0.77 macro precision, proving it could support data-driven, fair, and efficient officer deployment decisions, even with a small dataset.

The system was evaluated based on the ISO 25010 model and scored an overall weighted mean of 4.4. It performed best in Functionality and Usability, both scoring 4.5, indicating the system is effective and user-friendly. Performance also scored high (4.4), reflecting good responsiveness and capacity management. Slightly lower scores were seen in Reliability and Portability (4.3 each), which suggest the system could improve in handling unexpected issues and adapting to other platforms. Despite these, the system is considered high quality, efficient, and user-centric, with room for improvements in resilience and flexibility.

Both TODA drivers and STMO personnel rated the system as Highly Acceptable, with an overall weighted mean of 4.6. The highest scores were in Attitude Toward Using, with both groups strongly agreeing that "using this technology is a good idea." Perceived Usefulness also scored 4.7 across both groups, showing users believe the system improves task performance and productivity. The lowest—but still acceptable—score came from STMO personnel for "learning to use this technology" (4.4), indicating minor usability challenges during initial interaction. Over time, ease-of-use scores improved, and users expressed strong behavioral intention to use and recommend the system.

Using the Mann-Whitney U Test, researchers found no significant differences in technology acceptance between TODA drivers and STMO personnel. All p-values were above the 0.05 threshold, with the highest at 0.823 for Attitude Toward Using and the lowest at 0.548 for Behavioral Intention. This suggests that both user groups accepted the system similarly. An item-specific analysis, including Question 15 ($p = 0.417$), further confirmed uniform perception. The results indicate that the system design effectively met the needs of both administrative and operational users, consistent with the UTAUT2 theory, which states that clearly defined roles and supportive conditions lead to uniform technology acceptance.

B. Conclusion

The system's ability to grant officers immediate access to detailed violation records, coupled with automated penalty assignment, greatly improves consistency in law enforcement. By reducing manual workload and enhancing accuracy through centralized ticket data and the use of a unique Driver Control Number, the system ensures transparent and accountable operations in field enforcement.

This platform has proven valuable for administrators by offering real-time analytical tools that support data-driven planning. The ability to monitor frequent violations, analyze time-based trends, and track payment compliance empowers officials to make strategic decisions that enhance operational effectiveness and support sustainable enforcement initiatives.

By visualizing violation hotspots and patterns through an interactive map, the system strengthens the capacity of traffic authorities to act proactively. The addition of time, location, and code-based filters improves the precision of enforcement strategies, making location-based deployment more responsive to emerging public safety needs.

The integration of the Decision Tree V6 model demonstrates the practical application of machine learning in government operations. Its performance—marked by balanced accuracy, precision, and recall—shows the model's ability to support fair, efficient, and evidence-based officer scheduling, even with limited training data.

The ISO 25010 results highlight the system's strengths in functionality, usability, and performance, validating its role as a high-quality, user-centered solution. While minor enhancements in reliability and portability could broaden adaptability, the current quality metrics reflect a solid foundation for dependable and efficient use.

The strong acceptance ratings from both TODA drivers and STMO personnel affirm the system's alignment with user needs. Positive perceptions of usefulness and attitude toward usage confirm its relevance, while minor usability concerns during early use suggest the need for improved onboarding materials to further enhance user experience.

Finally, the statistical analysis confirms that both enforcers and end-users share a consistent level of acceptance for the system. The absence of significant differences between groups demonstrates that the design and implementation effectively addressed the expectations of all stakeholders, ensuring equitable usability and promoting widespread adoption.

C. Recommendations

Based on the results, the E-TRAVIO system should be accepted and made bigger so that it can be used in other cities with similar traffic control problems. For real-time violation detection, more study and system improvements should look into how to use IoT-based tools like surveillance cameras and automatic number plate recognition. To make E-TRAVIO easier for end users to reach, it is also suggested that a mobile app version be made. The decision tree model will be better at predicting officer deployment as long as it keeps collecting data and using the system. To get the most out of the software, the local government unit should make sure that users are regularly trained, that policies are aligned, and that the system is monitored. Finally, in the future, researchers may look into how E-TRAVIO affects traffic enforcement rates and the speed of government work over the long term to show that it works in a variety of local settings.

Also, to make sure the system is used consistently and safely, local traffic agencies should create written guidelines and standard operating procedures (SOPs). It's important to set up formal ways for users to give feedback so that system changes can use their ideas and experiences. Because the system has the ability to be an important part of smart government, LGUs should also look into policy support and budget allocation to keep it running and make it bigger. By doing these things, E-TRAVIO can help make roads safer, law enforcement more accountable, and people trusting local organizations more.

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