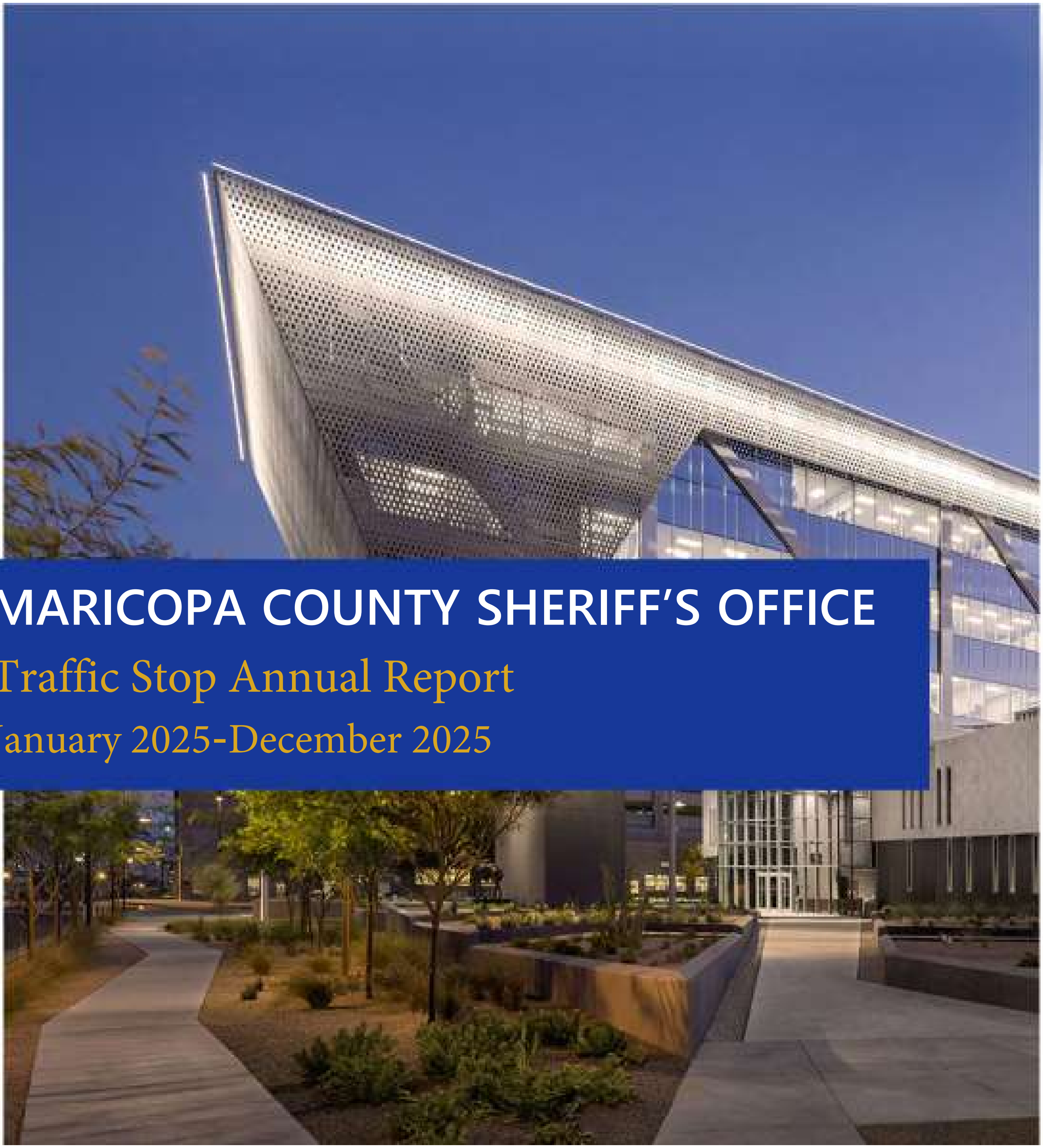

MARICOPA COUNTY SHERIFF'S OFFICE

Traffic Stop Annual Report

January 2025-December 2025

CNA

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Executive Summary

The Maricopa County Sheriff's Office (MCSO), established in 1871, serves and protects the unincorporated areas of Maricopa County, Arizona, and several cities to which the office provides law enforcement services on a contractual basis.[1,2] Since 2014, the MCSO has worked toward achieving compliance with four federal court orders requiring the MCSO to stop its immigration enforcement and refrain from using Hispanic ancestry as a factor in making law enforcement decisions. The MCSO currently operates under four related court orders, respectively titled the First Order, Second Order, Third Order, and Fourth Order. As a feature of the First Order, the MCSO must conduct organizational- and individual-level analyses of patrol activity to determine whether racial/ethnic disparities exist in MCSO traffic stop outcomes. This report provides 13 baseline analyses that looked for disparities in the outcomes of traffic stops. It compares the outcomes of Hispanic, Black, and all racial/ethnic minority drivers as a group to those of White drivers across five benchmarks: stop length, citation rate, search rate, arrest rate, and seizures following a search. In this report, we identify five disparate outcomes when compared to White drivers: a higher citation rate for Hispanic drivers; differences in arrest rates for Hispanic, Black, and all racial/ethnic minority drivers; and a statistically significant difference in the distributions of searches with and without seizures across driver race or ethnicity. Findings of statistical significance for certain benchmarks may guide which actions and efforts the MCSO prioritizes to address racial/ethnic inequality in traffic stops. Per the requirements of Paragraph 70 of the First Order, the MCSO continues to monitor and, when necessary, intervene to address any potential racial/ethnic bias across all the benchmarks.

Paul Penzone was elected Maricopa County Sheriff in November 2016 and took office in January 2017. In 2018, the MCSO contracted with the CNA Center for Justice Research and Innovation to analyze annual patrol activity and support the development of quarterly reports on special topics related to traffic stops. In January 2024, Penzone resigned his position as sheriff, and then Chief Deputy Russell Skinner was appointed sheriff by the Maricopa County Board of Supervisors for the remainder of the term. The current sheriff, Jerry Sheridan, was elected in November 2024 and assumed office on January 1, 2025.

This report examines patterns of patrol activity within the MCSO; it does not analyze or identify individual deputies.[3] This report analyzes all traffic stops made by MCSO deputies from January 2025 through December 2025. The MCSO uses all traffic stop reports to understand patrol activity in the office and as a foundation to inform potential interventions, initiatives, and new or revised policies. This work is being carried out in conjunction with the court-appointed Monitoring Team and Parties to the court orders (namely, the Department of Justice (DOJ) and American Civil Liberties Union (ACLU)).

The MCSO uses its Traffic and Criminal Software (TraCS) data system to capture data in the field from traffic stops. Of the hundreds of variables available through TraCS, we used a subset to analyze racial or ethnic disparities in stop outcomes. To accurately estimate the differential outcomes from traffic stops based on the race/ethnicity of the driver, we used two statistical approaches across the five relevant benchmarks: stop length, search rates, citation

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[1] Much of the material in this section is identical to the executive summary from the *Maricopa County Sheriff's Office Traffic Stop Annual Report: January 2024–December 2024*.

[2] MCSO investigated traffic patrol activity in contracted jurisdictions and county communities in *Traffic Stop Quarterly Report 16* (using 2023 traffic stop data) to identify whether certain jurisdictions evidenced disparity in traffic stop outcomes. Results of those analyses are available at https://www.mcsobio.org/_files/ugd/b6f92b_7bec34a3c24c4212bb86c9cb9fd4e35c.pdf

[3] The MCSO analyzes individual deputies' traffic stops through the Traffic Stop Monthly Report and review process.

rates, arrest rates, and seizure rates. We used propensity score matching to analyze stop length, search rates, citation rates, and arrest rates. *Propensity score matching* is a quasi-experimental method of statistical comparison that identifies the most similar events in a condition of interest—in this case, Hispanic, Black, or all racial/ethnic minority drivers[4] compared to White drivers—using a propensity score. To analyze seizure rates during searches, we used chi-square testing, which examines whether the racial/ethnic distribution of drivers subject to searches that result in seizures is different from the racial/ethnic distribution of drivers subject to searches that do not result in seizures.

MCSO deputies performed 24,647 traffic stops from January to December 2025. The rate of traffic stops per month was relatively steady throughout the year, with a slight increase in July 2025. The total number of stops in 2025 was 21.63 percent higher than in 2024. During the 24,647 traffic stops, deputies perceived approximately 65.35 percent of drivers as White, 23.31 percent as Hispanic, and 7.45 percent as Black. The remaining 3.90 percent of stops involved individuals from other historically marginalized groups, including Asian and Native American individuals. In the dataset, more than 72 percent of the stops lasted fewer than 15 minutes. Of the stops, 56.75 percent ended with a citation, 42.70 percent ended with a warning, and 5.72 percent ended with an arrest (including custodial and noncustodial arrests). Less than 1 percent of stops resulted in a non-incidental search of a driver or vehicle, meaning that the deputy decided to perform the search at their discretion.

The MCSO and the CNA analysis team conclude that there is evidence of disparity in two traffic stop outcomes between White drivers and the plaintiff class (Hispanic drivers), one traffic stop outcome between White drivers and Black drivers, and one traffic stop outcome between White drivers and all racial/ethnic minority drivers as a whole. Stops involving Hispanic drivers were more likely to result in a citation and an arrest than stops involving White drivers. Stops involving Black drivers were more likely to result in an arrest than stops involving White drivers. Stops involving all racial/ethnic minority drivers were more likely to result in an arrest than stops involving White drivers. In addition, we found a statistically significant difference in the distributions of searches with and without seizures across driver race or ethnicity. These disparities represent potential indicia of bias as described in the First Court Order, but they do not directly represent discriminatory policing, and they do not prove bias. The MCSO has been striving to reduce or eliminate disparities in traffic stop outcomes by using the Traffic Stop Monthly Reports (TSMRs) to identify individual deputies with the most disparate outcomes, enabling the MCSO to intervene when an indication of bias exists.[5] The MCSO is also using the Traffic Stop Quarterly Reports (TSQRs), which focus on specific areas with identified disparities, to develop actionable responses or identify sources of disparity observed in the traffic stop data. The MCSO began conducting quarterly research on traffic stops in 2020 and has released 22 quarterly reports. Since April 2021, the MCSO has generated 63 monthly reports. In addition, the MCSO evaluates policies and procedures continually and conducts 21 different inspections to ensure compliance with them. The MCSO also provides ongoing training designed to combat bias. Since 2023, the MCSO has been documenting internal reviews, Traffic Stop Annual Report (TSAR) results, and TSQR findings to give full transparency to all actions the MCSO considers and takes after each report. For additional discussion of findings from this and previous traffic stop reports, please refer to the conclusion section. The Monitoring Team and the Parties have not identified bias as the cause of the inequalities observed in our past annual reports.

The MCSO and the CNA analysis team collaborated to develop this report. Specifically, the MCSO was primarily responsible for collecting data, adjudicating missing values and data irregularities, and reviewing the annual report. The CNA analysis team was primarily responsible for developing and executing the analytical plan and writing the

[4] The "all racial/ethnic minority drivers" (referred to as "all minority drivers") analysis includes Hispanic, Black, Asian, and Native American drivers compared with White drivers.

[5] MCSO continues to conduct monthly analyses and reviews of deputy-level disparity in traffic stop outcomes.

annual report. The MCSO then drew conclusions from the analytical results and developed a response plan to address the findings. The analytical plan was developed collaboratively by CNA, the MCSO, the Monitoring Team, and the Parties.

The TSAR does not represent all of MCSO's efforts to identify and mitigate disparities. Through its quarterly reports, ongoing TSMR, and reviews of deputy activity, the MCSO is well positioned to identify disparities across these benchmarks that are the result of factors other than bias or discriminatory policing. Upon reviewing statistically significant TSMR findings, the Court Monitor has concurred with the MCSO that the inequalities in traffic stop outcomes identified in the TSMR process were not associated with bias or discriminatory policing. Understanding these findings is necessary to meaningfully interpret the results in this report. The MCSO and CNA will continue to work closely to analyze traffic stop activity by MCSO deputies, including developing additional annual analysis reports, monthly analysis reports focused on individual deputies, and quarterly reports on special topics as determined by the MCSO, CNA, and the Monitoring Team in consultation with the Parties.

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Introduction

Background

The Maricopa County Sheriff's Office (MCSO), established in 1871, serves and protects the unincorporated areas of Maricopa County and several cities to which the office provides law enforcement services on a contractual basis.[6] The MCSO includes more than 3,000 employees and provides enforcement and detention services to the nearly five million residents of Maricopa County. The MCSO operates the Fourth Avenue, Durango, Estrella, Lower Buckeye, and Towers jails; the Intake, Transfer, and Release facility; and smaller temporary holding facilities in district substations. The MCSO provides patrol and investigative operations for the county's six patrol districts, which include an array of businesses, residents, recreational areas, and communities. In addition, the MCSO operates specialized units and teams, such as specialized investigations, canine teams, and tactical operations.

Since 2014, the MCSO has worked toward achieving compliance with a federal court order entered in 2013 requiring the MCSO to stop its immigration enforcement and refrain from using Hispanic ancestry as a factor in making law enforcement decisions. In *Manuel de Jesus Ortega Melendres v. Arpaio* (now *Manuel de Jesus Ortega Melendres v. Sheridan*), a federal judge found that the MCSO violated the rights of Latinos in Maricopa County through racial profiling and a policy of unconstitutionally stopping persons without reasonable suspicion of criminal activity, in violation of their Fourth and Fourteenth Amendment rights. In 2013, Judge G. Murray Snow of US District Court, Arizona, issued the First Supplemental Court Order (First Order) to the MCSO to address the pattern of disparate treatment of Hispanic community members in Maricopa County. The First Order established actions required for the MCSO to attain compliance, including introducing new data collection and analysis requirements, training, and policies. The court appointed an independent monitor for oversight.[7] As a feature of the First Order, the MCSO must conduct organizational- and individual-level analyses of patrol activity to investigate racial or ethnic disparities in traffic stop outcomes. In 2018, the MCSO contracted with the CNA Center for Justice Research and Innovation to analyze patrol activity annually and produce quarterly reports on special topics related to traffic stops.

This report responds directly to the First Order requirement to analyze MCSO traffic stop activity to determine whether disparate outcomes exist between drivers of different races or ethnicities. This approach relies on propensity score matching to compare stops with similar characteristics other than the perceived race/ethnicity of the driver. This report examines patterns of patrol activity within the MCSO; it does not analyze or identify individual deputies. The MCSO analyzes individual deputies' traffic stop activity each month as part of its Traffic Stop Monthly Report (TSMR) process. This process has been ongoing since 2021. The MCSO expects to use this report as a knowledge base of traffic stop activity in the organization and as a guide for future research and potential interventions, initiatives, and policies. The MCSO is working collaboratively with the Monitoring Team and Parties to develop policies and activities to address racial/ethnic inequality related to MCSO's mission.

[6] Much of the material in this introduction is identical to the introduction in the *Maricopa County Sheriff's Office Traffic Stop Annual Report: January 2024–December 2024*.

[7] In 2016, the court issued the Second Supplemental Court Order (Second Order) to establish additional oversight and reforms for the MCSO. The Second Order does not include actions or requirements related to traffic stops. In 2022, the court issued a Third Order establishing requirements to address a backlog of misconduct investigations; in 2023, a Fourth Order clarified the timelines of those investigations. The Third Order and Fourth Order do not establish requirements related to traffic stops.

Purpose of traffic stop analyses

Analyses of patrol activities are becoming increasingly common across US law enforcement agencies. Law enforcement agencies face heavy scrutiny from the public and the media, who have concerns about bias and disparate outcomes by race/ethnicity in interactions between the police and community members. The interactions under scrutiny include officer-involved shootings, uses of force, searches, and traffic stops (see, for example, Baumgartner et al., 2021; Correll et al., 2007; Fridell & Lim, 2016; Fryer, 2016; Ridgeway, 2006; Ritter, 2017; Shoub, 2021). Although most law enforcement officers do not practice biased policing intentionally, they may exhibit behaviors that appear biased or that result from implicit bias (Bolas, 2022; Ekstrom et al., 2022; Marsh, 2009; Nix et al., 2017; Spencer et al., 2016; Stelter et al., 2022). Even though law enforcement strives for fair treatment, officers may unconsciously treat community members differently (Hall et al., 2016; Helfers, 2016; Roach et al., 2022; Stroshine et al., 2008). Of course, incidents involving explicit bias, such as racial profiling, have occurred in law enforcement practice, including the pattern of directed racial profiling that resulted in MCSO's court-ordered monitoring. Under Sheriff Sheridan's leadership, allegations of explicit bias are taken seriously and investigated thoroughly, and discipline (including termination) is meted out as quickly as possible.

Implicit bias refers to attitudes or stereotypes that affect understanding, actions, and decisions unconsciously (Staats et al., 2015). Officers' implicit biases may affect their interactions with a driver when making a traffic stop and may affect individual stop outcomes. This issue persists beyond the scope of law enforcement agencies—all people possess implicit biases, and implicit biases occur naturally on a subconscious level throughout society (Staats et al., 2015). Awareness of implicit bias provides law enforcement agencies with opportunities to work with organizations and researchers on methods and training to reduce implicit bias and its effects. Researchers have developed methods to identify officers who need implicit bias or other training through quantitative analysis of disparate outcomes. In contrast to implicit bias, *explicit bias* refers to conscious attitudes and beliefs (such as prejudice) about a person or group (James, 2018). In recent years, there has been a push for scholars and practitioners to reframe bias as a structural and systemic issue rather than as an individual issue. Although structural and systemic bias are closely related and the terms are often used interchangeably, they are distinct concepts. *Systemic bias* refers to overarching social systems that create and uphold inequality over time, such as the economy, health care, education, and criminal justice systems. *Structural bias* emphasizes the role of specific institutions, policies, and practices that operate within those broader systems, such as corporations, hospitals, schools, and courts (Braveman, 2022). Scholars in this area posit that individual-level implicit and explicit biases are byproducts of structural and systemic forces (Rucker & Richeson, 2021). Moreover, within biased systems, disparities can persist regardless of the attitudes of individual actors because bias is entrenched in everyday systems (Dovidio & Solomon, 2025; Payne, Vuletich, & Lundberg, 2017). For example, in women-dominated fields such as speech-language pathology and clinical psychology (in which the majority of students, faculty, practitioners, and leaders are women), graduate programs and workplaces still often lack adequate parental leave and comprehensive maternal health care. Within the context of law enforcement, even if every police officer held zero personal bias and enforced the law equally, racial and ethnic disparities would endure. Systemic racism is deeply embedded across the entire criminal justice continuum—from laws that disproportionately affect poor communities and communities of color (Santiago-Rivera et al., 2016; Gustafson, 2008), to biased civilian reporting in 911 calls (Han et al., 2024), to inequitable sentencing guidelines (Najdowski & Stevenson, 2022) and post-incarceration barriers (Jeffers, 2019; Western & Sirois, 2019). In addition to mitigating individual-level biases, understanding and treating bias as structural and systemic is necessary to uncover the root causes of inequality and create institutional reforms capable of producing meaningful, lasting change.

Over time, methods for identifying evidence of disparate outcomes have evolved. Early research on bias in policing and disparate stop rates or outcomes relied primarily on correlational and simple comparative methods (Gaines, 2006; Novak, 2004; Persico & Todd, 2006; Rodriguez et al., 2015; Smith & Petrocelli, 2001). Researchers now use methods such as propensity score matching and weighting to analyze traffic stops and other law enforcement activity outcomes for evidence of racial or ethnic disparity (Knode et al., 2024; Ridgeway, 2006; Riley et al., 2005; Tillyer et al., 2010). Methods for assessing disparities have evolved to incorporate measures beyond stop rates, focusing instead on stop outcomes, such as citations and searches (Christiani et al., 2022; Fridell, 2004; Fridell, 2005; Onookome-Okome et al., 2022; Tillyer et al., 2010). Researchers are also using more sophisticated benchmarks, moving away from population as an external benchmark for assessing disparate outcomes (Grogger & Ridgeway, 2006; Lange et al., 2005).

Understanding the expectations and limitations of quantitative analysis for investigating racial and ethnic disparities is important for interpreting the findings in this report. Research on traffic stops includes both pre-stop and post-stop analyses. Pre-stop analyses investigate whether the race/ethnicity of the driver affects stop rates; post-stop analyses investigate whether the race/ethnicity of the driver affects stop outcomes. The different limitations of these two analyses illustrate the difficulties of traffic stop analysis. A pre-stop analysis requires estimating the local driving population, which is a complex problem. Using census data is imprecise because such data include non-drivers and may not accurately reflect the driving population or the racial/ethnic distribution of drivers who violate traffic laws (McMahon et al., 2002; Ratcliffe and Hyland, 2025; Smith et al., 2021; Tregle et al., 2019). Other methods for estimating the racial/ethnic distribution of the driving population include observing and recording the race/ethnicity of drivers in a given jurisdiction over time or using driver's license race/ethnicity data. However, these methods can be cost-prohibitive or infeasible because of data unavailability (Fridell, 2004; Tillyer et al., 2010); for example, most states, including Arizona, do not capture race/ethnicity in their driver's license or registration documentation.

Post-stop analyses mitigate some of these issues because the population they capture is contained within the traffic stop data and does not need to be estimated (Ridgeway & MacDonald, 2010; Withrow et al., 2008). Post-stop analyses are not without their own limitations; for example, unobserved differences between groups can confound estimates of disparity (Ridgeway, 2006). In recent years, research and practical experience have increasingly highlighted the presence and effects of these unobserved factors. For example, differences in socioeconomic status, driving patterns, or prior interactions with law enforcement may not be fully captured in administrative data, yet they can meaningfully influence post-stop outcomes and the interpretation of observed disparities. A specific example of these unobserved differences can be seen in the MCSO's policy that mandates deputies to verify whether the driver has a valid driver's license at each traffic stop. The MCSO's historical analyses have consistently found that Hispanic drivers are more likely than White drivers to have a suspended license (Prelog et al., 2025). As a result, post-stop outcome disparities may partially reflect this underlying population difference rather than the actions or decision-making of the deputy.

Despite improvements in analytical methods, analysts still need accurate and in-depth traffic stop data from agencies to measure and identify disparate outcomes; the absence of adequate data can limit the scope of analysis and hinder analysts from recommending policy revisions to address disparities. Some agencies (such as MCSO) collect data from their traffic stops meticulously, whereas other agencies track only limited information, such as when a stop occurred, the driver's race/ethnicity, and limited stop outcomes. Agencies may also store data about traffic stops across data systems that cannot be linked readily.

Practitioners and consumers of bias research should understand that disparate outcomes do not definitively indicate that the biases that exist across society are the source of the disparity (Fridell, 2004; Simoiu et al., 2017). Quantitative analysis cannot capture all the possible reasons that could explain disparate outcomes. Even with these limitations, the results from statistical analyses can provide insight into policing practices in an agency, helping the agency identify disparate outcomes to address. Such analyses can also provide agencies with tools to review officer traffic stop conduct and determine the necessary actions, if any, for officers and agencies.

Many law enforcement agencies now analyze their traffic stop data internally or in partnership with external researchers and analysts. Most analyses conducted to date have found racial or ethnic disparities in traffic stop outcomes (e.g., searches, citations, arrests). Tillyer et al. (2010, pg. 70) state, "Analyses of these data demonstrate a relatively consistent trend of racial/ethnic disparities in vehicle stops and vehicle stop outcomes." Most existing studies have found evidence of racially disparate stop rates or outcomes of patrol activity in law enforcement agencies (Ariel & Tankebe, 2018; Barnum & Perfetti, 2010; Baumgartner et al., 2018; Engel & Calnon, 2004; Gaines, 2006; Gelman et al., 2007; Hannon et al., 2020; Iwama & McDevitt, 2025; Norris et al., 1992; Novak, 2004; Pierson et al., 2020; Roach et al., 2022; Rodriguez et al., 2019; Rojek et al., 2004; Rosenfeld et al., 2012; Shoub, 2025; Smith & Petrocelli, 2001; Stelter et al., 2022; Taniguchi et al., 2017; Tillyer & Engel, 2013; Vito et al., 2020; Webb et al., 2021; Weiss & Rosenbaum, 2006). A few studies have found no racial or ethnic disparity in traffic stop outcomes (Fallik & Novak, 2011; Grogger & Ridgeway, 2006; Higgins et al., 2012; Iwama, 2024; McCabe et al., 2020; Taniguchi et al., 2016; Zhang & Zhang, 2021). The balance of the evidence suggests that disparate outcomes during traffic stop activity are common in law enforcement agencies in the United States; however, acknowledging the prevalence of the problem does not imply that agencies should not address disparate outcomes pragmatically and proactively by promoting anti-bias policy, training, and practices.

The MCSO currently combats biased policing through ongoing enhanced trainings, continual policy reviews and revisions, a series of inspections that include a statistical review of every deputy's traffic stops each month, and an early intervention system to help supervisors identify and intervene in potentially problematic behaviors. In addition, the MCSO's Community Outreach Division is involved in community policing and recruitment efforts in the communities that the MCSO serves. In response to the findings from last year's *Traffic Stop Annual Report 10*, the MCSO conducted the following activities: communicated results to employees and the public through town halls and its website, provided Monitor-approved enhanced training to personnel to address the findings in TSAR 10, developed an information dashboard to help identify areas where patrol should focus on improving traffic safety, developed a traffic stop review dashboard to enable supervisors to review stops conducted by deputies, validated the use of extended stop indicators, analyzed disparities both within and between districts, and explored data continuously to understand disparities and potential ways to mitigate them. MCSO also investigated citation and arrest disparities in quarterly reports this year in addition to the ongoing (monthly) TSMR process, whereby each deputy's traffic stops are analyzed and an investigative review is conducted if statistically significant disparities are identified. None of these reviews have found deputy bias to be the cause of observed disparities.

The use of statistical analysis for identifying racial/ethnic disparities in traffic stops has become increasingly crucial, and previous analyses have indicated that disparities exist across the nation. The MCSO has been and continues to be committed to ongoing research to identify responses to help address those disparities where it can. The MCSO is at the forefront of analyzing racial/ethnic disparities in traffic stop outcomes in the United States, and no other policing agency in the country conducts as extensive and in-depth analyses of racial/ethnic disparities in policing.

Organization of this report

This report is organized into four sections: introduction, approach, findings, and conclusion. The approach section explains the MCSO's and CNA's methods for analyzing traffic stop outcomes and developing this report. The findings section details the results of the traffic stop analysis on the selected outcomes. The conclusion section reviews the analytical findings, discusses ongoing and future activities that the MCSO is or will be conducting in response to these findings, and recommends future analyses that the MCSO and CNA will conduct in response to the First Order. The appendixes provide a reference list and a list of abbreviations.

In addition, we provide supplemental appendixes to this report in a separate companion document, including supporting data tables, alternate propensity score matching models, and analytical support and robustness checks. The appendixes also include deprecated analyses related to previous TSARs. We provide these analyses to allow additional comparisons in order to identify other potential influences on traffic stop outcomes. We reference the deprecated statistical models throughout the report if they produced results that were different from the Monitor's approved baseline models. Law enforcement researchers and analytical practitioners looking to implement similar studies in other agencies will likely find these appendixes of interest.

APPROACH

In this section, we discuss the data, variables, and methodology that we used in the traffic stop analysis. We begin by describing the MCSO Traffic and Criminal Software (TraCS) data system, defining the variables used in the analysis, and describing the data cleaning process that we performed before analysis. We then discuss the propensity score matching approach that we used to assess racial/ethnic disparity in stop length, search rates, citation rates, and arrest rates, as well as the chi-square analysis that we used to assess racial/ethnic disparity in seizure rates. We also discuss the alternate specifications that we used for the propensity score matching analyses. We close by noting specific considerations for interpreting the findings from this analysis as well as limitations of the approach.

Overview of data and variables

TraCS is a data collection, records management, and reporting software for public safety professionals. The MCSO uses TraCS to capture data about traffic stops. Deputies use TraCS to document aspects of traffic stops, including driver and vehicle characteristics and activities that occur during the stop. TraCS captures the start time, end time, and GPS location of each traffic stop.[8] The system also requires the deputy to enter variables such as the perceived race/ethnicity of the driver,[9] the contact conclusion, whether an arrest took place, and search and seizure information. TraCS also includes data fields for capturing information about any delays during the stop, such as training, driving under the influence (DUI) investigations, vehicle tows, technical issues, language barriers, driving documentation issues, or other issues, and it includes a comment field for deputies to input additional information.[10] After the deputy fills out information about events in TraCS, the system forwards entries for supervisory review and, if necessary, revision. We used a subset of the several hundred variables available in TraCS to analyze racial or ethnic disparities in stop outcomes, and we constructed and appended data using variables present in TraCS and other MCSO systems. Here, we briefly describe the variables that we used in the analysis and those constructed by the analysis team. For all categorical variables coded into a single variable (such as stop classification or the perceived race/ethnicity of the driver), we constructed indicator variables for each category.

Data about the stop

We used the stop date, stop start time, and stop end time variables to develop descriptive information about stops conducted by the MCSO. We also used the stop start and end times to construct the stop length variable, which codes how long a stop lasted, in minutes, from reported start to finish. The stop classification summarizes the violation, per the Arizona Revised Statutes (ARS), classified into five categories: civil, criminal, civil traffic, criminal traffic, and petty. Although there are multiple categories, we used criminal traffic as the reference with all other clarifications as the comparison conditions. We also included the specific violation category, coded as speed, non-speed moving, equipment, license/insurance/registration issues, and other violations. Deputies can also indicate whether circumstances beyond their control extended the length of a stop, including technical issues (e.g., a printer

[8] In some patrol areas, particularly within Lake Patrol's jurisdiction, GPS coverage can be inconsistent. In these cases, TraCS may not automatically capture the GPS coordinates of the stop. We discuss this issue further in the section on missing data.

[9] Arizona does not collect information about race/ethnicity as part of its driver's license system; thus, all race/ethnicity categories within TraCS data are based on the perception of the deputy who made the stop.

[10] A detailed description of the TraCS data collection system and included variables is available in MCSO policy #EB-2, "Traffic Stop Data Collection," available publicly on the MCSO website: https://www.mcso.org/about-us/general-info/mcso-policies

failure), a language barrier, a DUI stop, training, time spent calling for a tow, or time spent verifying documentation (e.g., a driver without their insurance card verifying their insurance by phone). We also included a variable capturing information about the deputy's assignment (based on call sign) categorized as normal patrol, Lake Patrol, off-duty assignment, designated traffic stop car (or motorcycle), supervisor, and other. For analyses presented in Supplemental Appendix 5, we identified whether the stop occurred as part of a special assignment, such as the DUI Task Force or Aggressive Driving Task Force. We also included a variable that indicates whether a particular stop was for a speeding offense; if so, we included a categorical variable indicating the number of miles per hour over the posted speed limit.

Data about stop outcomes

Stop conclusion data describe the outcome of the stop as a citation, warning, or incidental contact. TraCS indicates whether a stop included a search of the driver or vehicle (we omitted passenger searches from this analysis because our focus was on drivers) and whether that search was incident to arrest or towing.[11] We constructed a variable that indicates whether a search of the driver or vehicle took place. For this analysis, we restricted our interest in searches to those that were non-incidental (i.e., discretionary). For example, policy dictates that all individuals be searched before custodial arrest and courtesy rides and that all vehicles be inventoried before tow; searches that occur incidental to arrests, courtesy rides, or inventory searches for vehicle tows are not discretionary and were thus excluded from our analysis of search outcomes. Deputies also indicate in TraCS whether a search resulted in the seizure of contraband.

Data about the driver

We used the post-stop perceived race/ethnicity of the driver, as entered by the deputy, to classify the driver's race/ethnicity as Asian, Black, Hispanic, Native American, or White. We also used the post-stop perceived sex of the driver to create an indicator variable for male drivers (with female drivers and drivers of unknown sex collapsed as the comparison category). We also included the reported license plate state of the vehicle that the driver was operating, classifying it as either an in-state or out-of-state plate.

During the time frame of this analysis, the special assignments included the DUI Task Force, Click-It-or-Ticket Task Force, and Aggressive Driver Task Force. For descriptive purposes, the analysis team also constructed a deputy traffic stop count variable equal to the number of stops that the deputy made over the 12-month period.

Data verification and missing data

The analysis team reviewed the 2025 TraCS data for data quality (e.g., missing data, out-of-range values) and verification.

The analysis team identified additional missing data that the MCSO could not adjudicate. For example, one stop lacked data on perceived driver race/ethnicity because the driver fled and the traffic stop was never completed. These missing data represent less than 1 percent of the overall data, which is under any standard threshold that would trigger concerns about missing data biasing the analysis or findings. Supplemental Appendix 1 describes the missing data by variable.

In addition, the analysis team verified GPS coordinates using crossroads and mile markers. We also corrected arrest information based on the ARS codes for misdemeanors.

[11] A detailed analysis of search activity during traffic stops is available in *Traffic Stops Quarterly Report 10: 2022 Searches*, https://www.mcsobio.org/_files/ugd/b6f92b_8fd0a6175a6f4d6483a8d97fa75f4d42.pdf.

In addition, TraCS offers additional lines to capture data about multiple contacted passengers; because our analysis focused solely on drivers, we did not include the data from these lines in our analyses. We identified these entries based on the event number, deputy's badge number, and driver's first and last name, and we then removed them.

Methodology

To accurately estimate differential outcomes from traffic stops based on the perceived race/ethnicity of the driver, we used two statistical approaches across the five benchmarks under consideration. To analyze the stop length, search rates, citation rates, and arrest rates, we used propensity score matching. To analyze seizure rates during searches, we used chi-square testing and Fisher's exact test. We discuss each of these approaches in more detail in this section.

Propensity score matching is a quasi-experimental method of statistical comparison. Researchers use quasi-experimental methods in circumstances in which random assignment (i.e., experimental approaches) is not feasible or practical; these techniques leverage specific data structures and statistical techniques to approximate experimental conditions (Shadish et al., 2002). In this case, propensity score matching matches individual events (i.e., traffic stops) with similar events based on their characteristics (listed in the next paragraph). Specifically, propensity score matching identifies the most similar events in or not in a condition of interest (in this case, Hispanic, Black, or all racial/ethnic minority drivers[12]) using a propensity score (Apel & Sweeten, 2010; Rosenbaum & Rubin, 1983).

For this traffic stop analysis, we used the first stage of propensity score matching to determine the probability that a stop involved a driver of a particular race/ethnicity (i.e., Hispanic, Black, and all minorities). For all analyses, stops involving White drivers served as the comparison conditions. We performed matching analyses using the observed characteristics of the stop—specifically the driver's sex, the stop longitude and latitude, the stop time, the stop classification (operationalized as civil traffic stops versus all others for all analyses, excluding arrests[13]), the violation type, whether the vehicle had out-of-state plates, the miles per hour over the speed limit for speeding offenses, whether the deputy indicated that the stop was extended for one of the reasons discussed in the previous section, and the call sign category under which the deputy was operating.[14,15] As an alternate specification, we also considered each model with the inclusion of special assignments as a matching variable. In addition, for the stop length analysis only, we included whether the stop involved an arrest or a search (both circumstances necessarily result in longer stops). For the stop length analysis, we also matched on extended stop indicators because the MCSO's *Traffic Stop Quarterly Report 21: Extended Traffic Stop Indicator Use* verified that deputies are using extended stop indicators appropriately.[16] For citation outcomes, we also included the stop category and a variable indicating whether the stop was pursuant to ARS 28-3151A.[17]

To obtain the propensity scores, we used a logistic regression model with elastic net regularization. Regularization prevents model coefficients from growing too large; it is a common tool used to prevent a model from "overfitting" to

[12] The "all racial/ethnic minority drivers" analysis includes Hispanic, Black, Asian, and Native American drivers compared with White drivers.

[13] MCSO altered the analyses of arrests for last year's annual report (TSQR 10). In previous reports, analyses of arrests included matching on stops that were classified as civil and criminal. Because all stops classified as criminal are also arrests, this variable was removed from the matching process for analyses of arrests.

[14] Both stop time and stop location are fitted using splines to allow for a more flexible functional form.

[15] The logistic regression also included interaction terms for stop location, and between the speeding violation variable and the categorical variables capturing the speed recorded over the speed limit.

[16] Report available here: https://www.mcsobio.org/_files/ugd/b6f92b_624516127a9d44898ac44f9ab2788e8c.pdf.

[17] ARS 28-3151A indicates that individuals should not drive without a valid driver's license.

the data. It is especially useful for models with many features or with features that are strongly correlated (which is the case here). Logistic regression models use two common types of regularization: LASSO, which tends to set certain coefficients to zero (thus eliminating features from the model entirely), and Ridge, which tends to make certain coefficients very small but rarely exactly zero. Elastic net is a combination of Ridge and LASSO and requires the analyst to provide two "hyperparameters." One controls how much regularization to apply, and the other controls whether the model behaves more like LASSO or more like Ridge regression. To obtain these hyperparameters, we performed a grid search across possible pairs of candidate values and evaluated each pair using five-fold cross-validation. For each model, we chose the pair resulting in the lowest validation error across the five folds. We then used this pair to fit a regularized logistic regression model on the entire dataset, and we used the fitted values for that model as the propensity scores.

Cross-validation is a common method for evaluating model settings. The dataset is split into five "folds," with each data point appearing in a single fold. The model is fit five times for each candidate setting. In each case, one fold is withheld from the dataset, the model is trained on the other four folds, and the model is then evaluated on the withheld fold. The objective function that we used to evaluate model performance on each fold is cross-entropy error, also known as deviance. The setting that resulted in the best average performance across all folds was then used to fit the model on the entire dataset.

After this matching step, we conducted comparisons using the propensity scores to match observations. For the baseline analysis presented in the main body of this report, we used nearest neighbor matching (in which stops in the condition of interest are compared by propensity score with the nearest one stop that is not in the condition of interest). We chose nearest neighbor matching as the baseline case because it is the least susceptible to problems with achieving common support (Caliendo & Kopeinig, 2005), a necessary condition for validating propensity score matching results. Supplemental Appendix 6 presents common support and results from common support testing in more detail. To check the robustness of our results, we ran each analysis using radius matching (in which stops in the condition of interest are compared with all stops within a certain propensity score range that are not in the condition of interest) using multiple radii values. Finally, we used nearest N-neighbor matching (in which stops in the condition of interest are compared with the nearest N stops by propensity score that are not in the condition of interest). We also matched with and without replacement as a sensitivity check. Supplemental Appendix 5 presents detailed results from the robustness check analyses.

For all analyses, we present findings in terms of the average treatment effect on the treated (ATT), that is, the average difference in outcomes between those who receive treatment. In this report, the ATT reflects the difference between outcomes in stops involving Hispanic, Black, or all racial/ethnic minority drivers versus those involving White drivers. We report the ATT as a measure of difference between Hispanic, Black, and all racial/ethnic minority drivers when compared to White drivers. To avoid confusion, *treatment* and *treated* in this context are terms derived from experimental methods identifying the treatment and control groups. In the context of the analyses presented in this report, *treatment* and *treated* refer to the racial or ethnic group analyzed and do not refer to deputies' interpersonal interaction with drivers. We conducted standard checks of balance and common support for all propensity score analyses. We summarize these results in the body of the report and present them in detail in Supplemental Appendix 4.

We analyzed seizure rates during searches using a standard chi-square test of homogeneity across mutually exclusive categories (in this case, perceived race or ethnicity). This test uncovers whether seizure rates vary significantly across racial or ethnic categories. As noted in the literature, different rates of seizures may indicate racial or ethnic bias because differences suggest that deputies may use different decision criteria or thresholds before searches of drivers of different races or ethnicities (Persico & Todd, 2006; Ridgeway & MacDonald, 2009; Simoiu et al., 2017; Walker, 2003). For this analysis, we considered only discretionary searches. We used a standard chi-square analysis with Pearson's and likelihood ratio tests (Pearson, 1900). We also ran Fisher's exact test (because of the small number of stops of Asian and Native American drivers) for comparison purposes.

Alternate specifications

As noted previously, we varied the propensity score approach for the propensity score matching analyses to encompass two matching methods: radius and neighbor. We also varied the parameters used for the radius caliper size and the number of neighbors matched. Finally, we considered the effect of allowing replacement (i.e., whether an observation can be used to match multiple other observations) for nearest neighbor and radius matching.[18] The supplemental appendixes to this report present the results from the alternate specifications. In the supplemental appendixes, we provide additional alternate specifications for stop length, citations, and arrests, which we analyzed using variations on the variables used in the analyses. All parties agreed upon the baseline analyses; to ease the interpretation of results, we present only baseline analyses in the main body of this report and provide all deprecated and alternate specifications in the supplemental appendixes. We note in the main body of the report when the results from the baseline analyses and deprecated model specifications are different.

Considerations and limitations

Propensity score matching represents a substantial improvement over past methods of estimating racial/ethnic disparity in law enforcement activities because it does not rely on the development of imperfect or cost-prohibitive external benchmark data and it more precisely estimates the differences in outcomes when accounting for differences in circumstance among interactions (e.g., traffic stops). However, the methodology is not without limitations. Propensity score matching does not directly measure bias or racial discrimination. Instead, the method identifies indicia of potential bias by measuring unequal outcomes. The models do not account for the unobserved characteristics of the driver or the stop; for example, they do not capture whether the driver committed multiple violations or when additional violations (e.g., license, insurance, or registration violations) were identified during the stop. This limitation can result in inaccurate estimates of treatment effects. The model also cannot account for any variable that perfectly predicts the condition of interest, such as DUI violations, or control for confounding characteristics of traffic stops not included in the models (Ridgeway, 2006; Rosenbaum and Rubin, 1983).

Another limitation is the potential for model dependence because findings may vary based on modeling choices (e.g., matching variable selection). Although the MCSO and CNA sought to select reasonable and theoretically grounded base models, alternate specifications have the potential to produce different results (see Appendixes 3 through 5). Furthermore, this TSAR introduced additional matching variables that resulted in a reduced effective sample size because not all observations in the original dataset have a suitable match.[19] Specifically, introducing the ARS 28-3151A variable as a matching variable reduced the effective sample size of White drivers for the citations outcomes. This limitation was discussed with the Monitors and the Parties during the February 2025 site visit.

[18] Matching without replacement cannot be feasibly conducted on N-to-1 neighbor matching analyses.

[19] For example, for the model comparing Hispanic drivers to White drivers stop lengths, 16,025 stops of White drivers were matched to 5,703 stops of Hispanic drivers. These comparisons for the remaining model can be found in Appendix 5.

Finally, as with all statistical techniques used to assess outcomes and behavior from law enforcement personnel, the results from these analyses can uncover only evidence of disparities in outcomes based on race or ethnicity; on their own, the results cannot provide insight into the underlying causes of these disparities.

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Findings

In this section, we begin by describing the included variables. As part of the descriptive statistics, we present the traffic stop rates by the race/ethnicity of the driver. The analysis team worked closely with the MCSO to assess various options for external benchmarks to use as a comparison condition for stop rates by race/ethnicity. Most existing or proposed external benchmarks (e.g., census populations) provide inaccurate estimates of the driving population or are impractical and cost-prohibitive (e.g., collecting data on driver race/ethnicity using observations at intersections). We considered several emerging practices (e.g., comparing daytime versus nighttime stop rates, using accident data, comparing criminal versus civil traffic stop rates), but we could not implement them using the currently available data from the MCSO or other sources, such as Arizona driver's license information. Therefore, we present only descriptive statistics for stop rates.

We present the findings from the comparative propensity score matching and chi-square test of homogeneity in the following subsections. For each stop outcome we analyzed using propensity score matching, we include the results from comparing Hispanic drivers to White drivers, comparing Black drivers to White drivers, and comparing all racial/ethnic minority drivers to White drivers. We did not specifically analyze Asian or Native American drivers because of the relative sparsity of stops involving these drivers. The chi-square analysis includes drivers of all races and ethnicities.

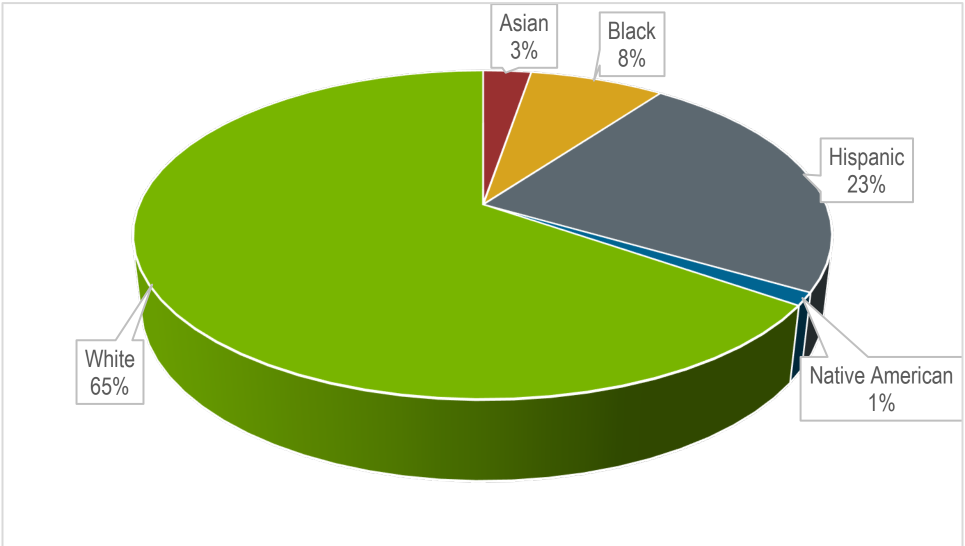
Descriptive statistics

In this section, we describe the data included in this analysis of traffic stops conducted by the MCSO between January and December 2025 (a 12-month period). We present the stop characteristics, the characteristics of the stop outcomes, and the traffic stop count of the deputies making the stops. Supplemental Appendix 1 provides a full table of descriptive statistics for each variable.

Driver characteristics

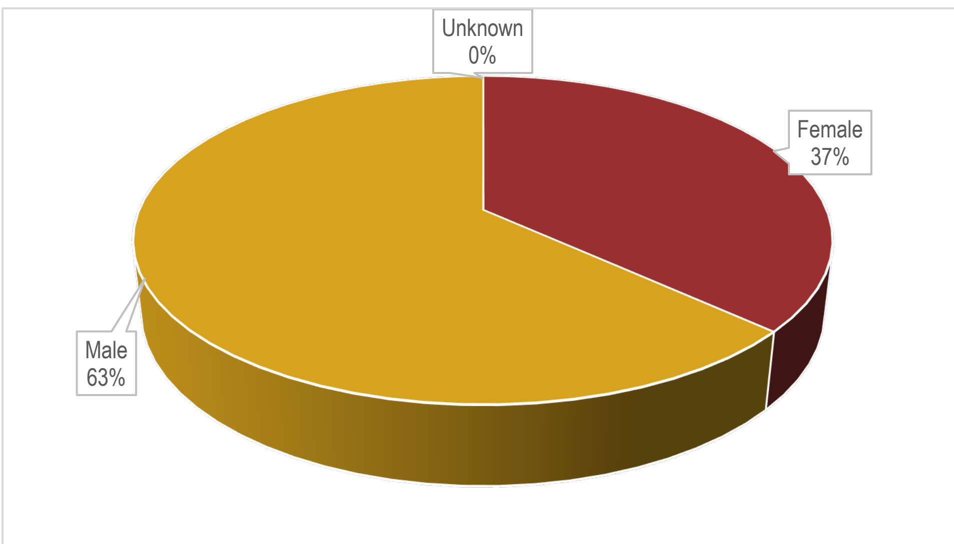
When deputies make a traffic stop, they document their observation of the perceived race/ethnicity of the driver both pre- and post-stop in TraCS. Deputies do not ask drivers questions about race/ethnicity during stops, and that information is not provided on Arizona driver's licenses. We omitted analysis of the pre-stop perception of driver race/ethnicity because this variable takes the value "unknown" in approximately 98 percent of stops. Post-stop, deputies perceived approximately 65 percent of drivers as White, 23 percent as Hispanic, and 8 percent as Black. The remaining 4 percent of stops were of Native American and Asian drivers (Figure 1).

Figure 1. Stops by post-stop perceived driver race or ethnicity



The deputies also enter post-stop perceived sex in TraCS. Deputies perceived 63 percent of drivers as male and 37 percent as female. In one stop (less than 1 percent), the deputy could not determine the sex of the driver (Figure 2).

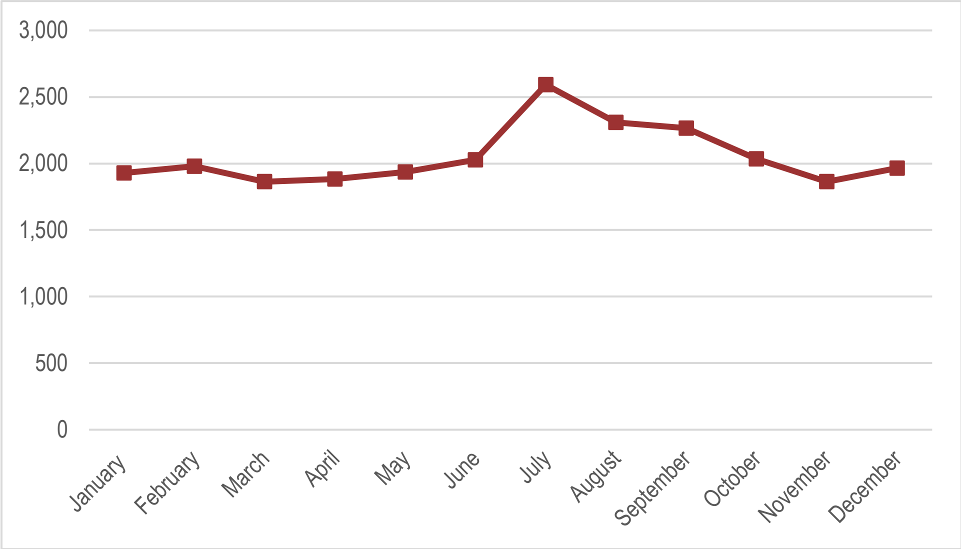
Figure 2. Stops by post-stop perceived driver sex



Stop characteristics

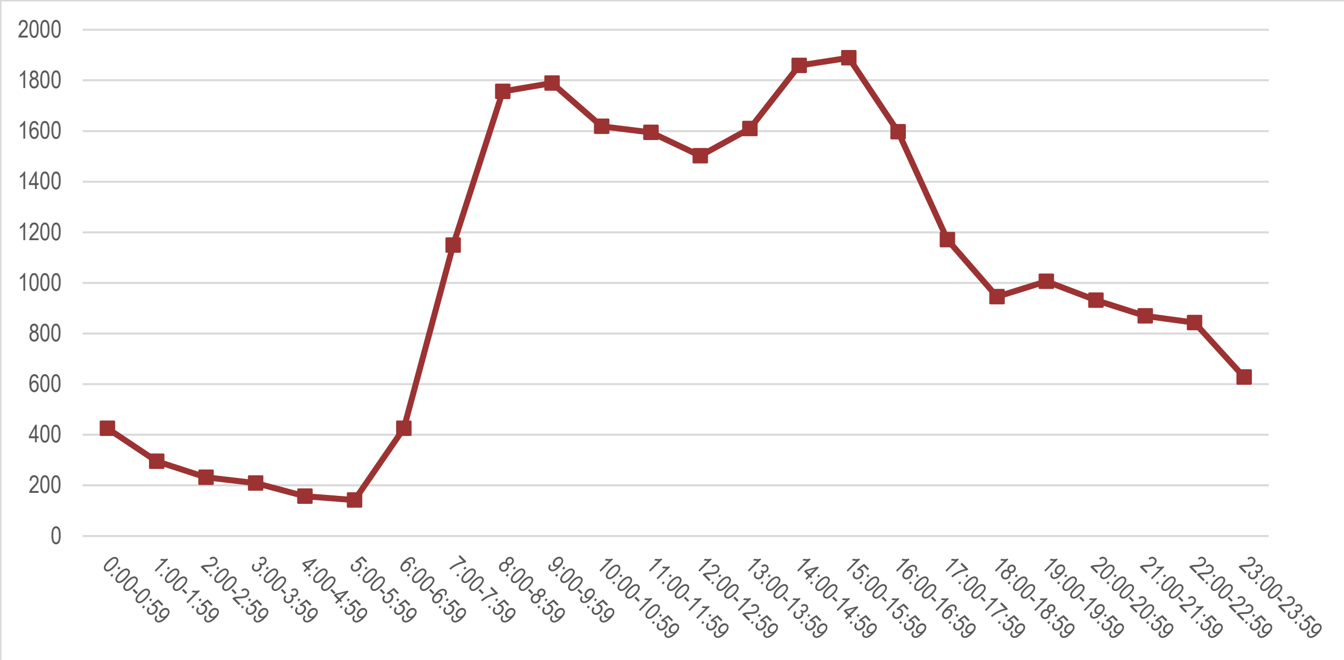
MCSO deputies performed 24,647 traffic stops during the 12-month period observed for this analysis. Monthly traffic stops remained relatively consistent between January and May 2025. Traffic stops increased between May and July 2025 and then decreased throughout the rest of the year (Figure 3). This overall trend is different from what we observed in 2024, when we saw a decrease of traffic stops in June 2024. Traffic stops in 2025 increased by approximately 22 percent compared to the number of stops in 2024 (n=20,265).

Figure 3. Stops by month, January to December 2025



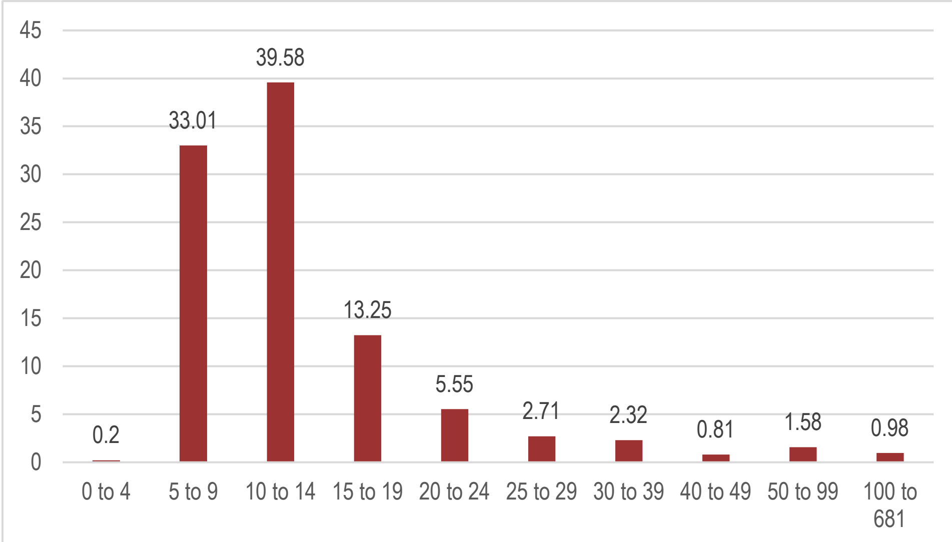
We also considered the time of day that a stop took place. Most stops occurred between 7:00 a.m. and 8:00 p.m., which was similar to trends in previous years. After 7:00 p.m., there was a steady decrease until 6:00 a.m. (see Figure 4).

Figure 4. Stops by time of day



Stop length is particularly important to this analysis because it is a core aspect of the court order. Stops lasted an average of 15.16 minutes (with a standard deviation of 18.44 minutes), a 5.19 percent decrease from the annual report on the 2024 data (in which the average stop length was 15.99 minutes with a standard deviation of 22.19 minutes). Most stops lasted between 5 and 14 minutes (Figure 5).

Figure 5. Stop length, in minutes



Deputies document in TraCS whether a stop was extended for reasons that would reasonably extend a stop. The extended stops field contains seven options: DUI stop, language barrier, technical issues, training stops, vehicle towed, driving-related documentation issues, and other issues. Deputies selected extended stop indicators for 13,631 stops, representing 55.30 percent of total stops; this finding reflects an increase from the previous annual report, in which extended stops represented 50.30 percent of total traffic stops.[20] Note that deputies may select more than one extended stop indicator during the stop. The most frequent reason for an extended stop was documentation issues (43.64 percent), and the next most frequent reason was other issues (17.49 percent). This finding was similar to that in the previous year's report, in which documentation and other issues were also the most common reasons for extended stops (Table 1).

Table 1. Extended stop reasons

Reason Indicated	Count of Stops	Percentage of Stops
DUI stop	417	1.69%
Language barrier	612	2.48%
Technical issue	2,305	9.35%
Training stop	1,097	4.45%
Vehicle towed	444	1.80%
Documentation issue	10,757	43.64%
Other issue	4,311	17.49%

We also considered which stops occurred while the deputy was on a special patrol assignment. Of the 24,647 stops in the dataset, 786 stops occurred while deputies were on DUI Task Force assignment, 1,220 occurred while deputies

[20] The MCSO has investigated extended stop indicator use with 2020, 2023, 2024, and 2025stop data in *Traffic Stops Quarterly Reports* 3, 13, 17, and 21 which can be found here: https://www.mcsobio.org/traffic-stop-data

were on the Aggressive Driver Task Force, and 67 stops occurred while deputies were on the Click-it-or-Ticket Task Force (Table 2).

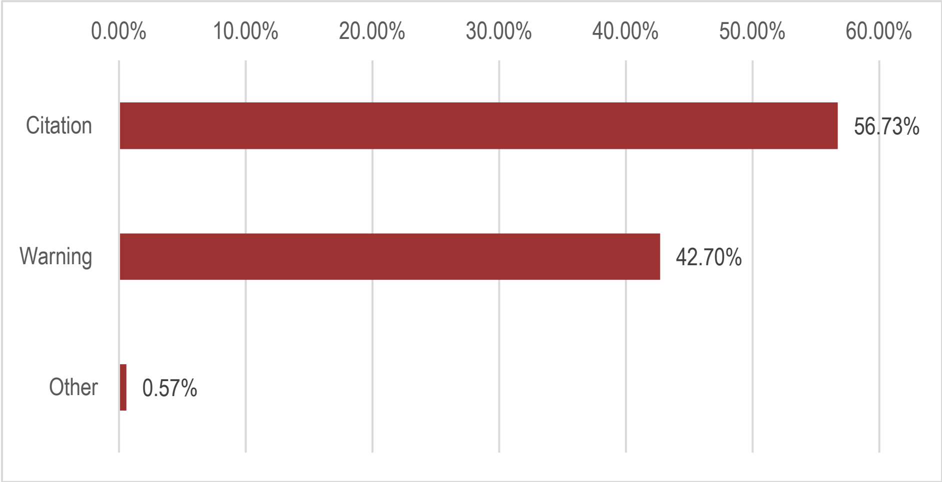
Table 2. Stops conducted during special assignments

Special Assignment	Count of Stops	Percentage of Stops
DUI task force	786	3.19%
Aggressive driver	1,220	4.95%
Click-it-or-ticket	67	0.27%

Stop outcomes

Contact conclusion documents the outcomes from each stop. Of all traffic stops, 56.73 percent concluded with a citation, 42.70 percent concluded with a warning, and less than 1 percent concluded with non-enforcement outcomes or an incidental contact, which may occur if a deputy is preempted for a priority call and ends the traffic stop without issuing a citation or documented warning (Figure 6).[21]

Figure 6. Traffic stop contact conclusions



Unlike in 2024, White drivers were cited at higher rates than both Black and all racial/ethnic minority drivers and at slightly lower rates than Hispanic drivers (Table 3).

[21] This citation rate has increased over the TSARs in recent years. For example, TSAR 8 reported a citation rate of 51.6 percent, and TSAR 9 reported a citation rate of 52.27 percent. With the increase in citations, MCSO has reported decreased disparities in citation rates.

Table 3. Traffic stop contact conclusions by race/ethnicity

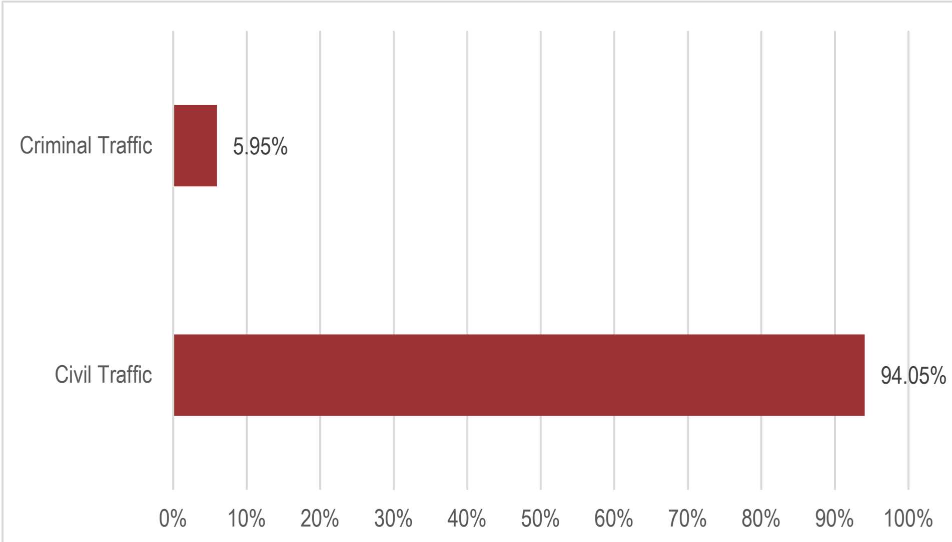
Race or Ethnicity	Citation		Warning		Other	
	Count	Percent	Count	Percent	Count	Percent
White drivers	9,161	56.88%	6,864	42.62%	81	0.50%
Hispanic drivers	3,338	58.10%	2,365	41.17%	42	0.73%
Black drivers	948	51.66%	873	47.57%	14	0.76%
Minority drivers	4,821	56.45%	3,660	42.85%	60	0.70%

The MCSO categorizes traffic stops into five categories based on ARS code: civil traffic, criminal traffic, petty, civil, and criminal. In 2025, all stops were either civil traffic or criminal traffic stops.[22] Most stops were civil traffic stops. Civil traffic violations are violations in which the driver does not face jail time and instead may be subject to a fine. Examples include speeding, equipment violations, and seatbelt violations. Criminal traffic violations are traffic violations that result in a fine and involve possible jail time. Examples include criminal speeding, reckless driving, DUI, and driving with a revoked or canceled license. All criminal or criminal traffic violations are considered arrests whether the driver was taken into custody or not. Petty violations are criminal violations with less severe penalties that do not include the possibility of jail time. Examples include boating violations, park violations, and curfew violations.[23] Criminal violations, which for the purposes of this report are grouped with criminal traffic violations, refer to non-traffic offenses that involve possible jail time and are typically discovered during a traffic stop—such as when a deputy stops an individual for a traffic violation and identifies unrelated criminal activity. Warrant arrests, however, are not classified as criminal violations; deputies cite or warn for the original violation and classify it according to the specific type of violation. Of the 2025 traffic stops, 94.05 percent resulted in a civil traffic classification, and 5.95 percent resulted in a criminal traffic classification (Figure 7).

[22] MCSO had a small number stops that were criminal, but these were classified as criminal traffic for this report. There were 25 stops in 2025 with only criminal violations. Criminal stops are often coupled with criminal traffic stops. For example, a driver might be cited for a DUI (criminal traffic but has an open alcohol container in his/her vehicle (criminal).

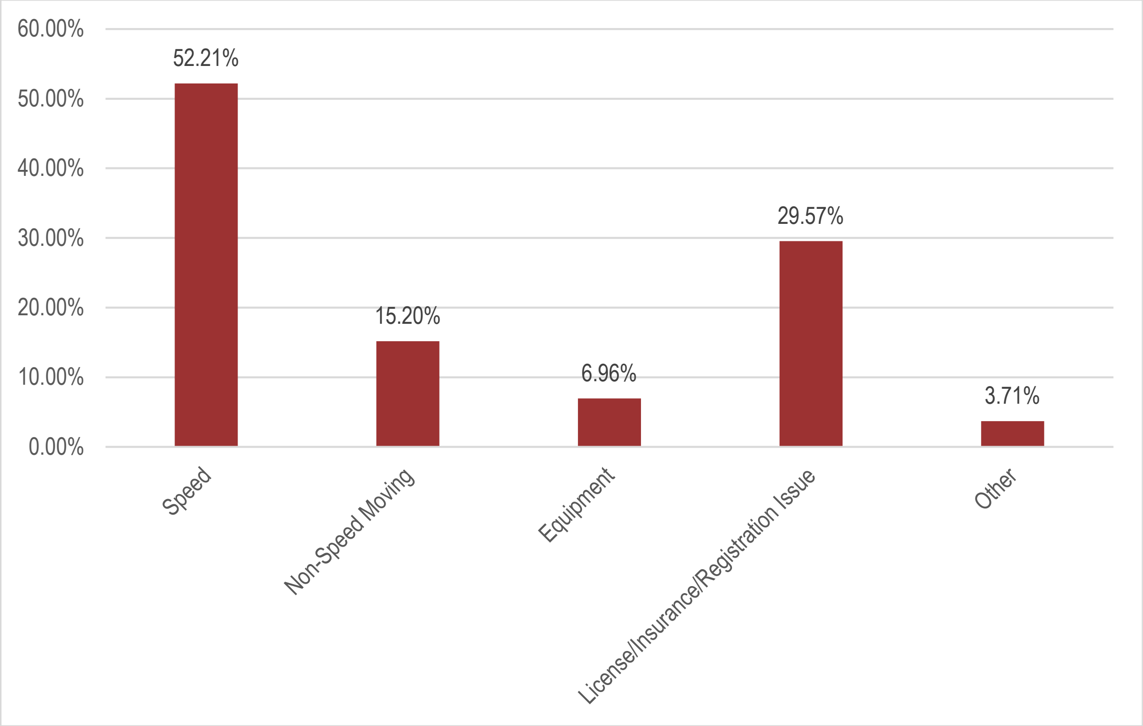
[23] There were no petty violations during traffic stops in 2025.

Figure 7. Traffic stop classifications



The MCSO categorizes traffic stops into five violation categories: speed, non-speed moving, equipment, license/insurance/registration issues, and other violations. These violation categories were derived from ARS sections and subsections. Speeding violations are violations associated with exceeding the speed limit (e.g., civil speeding, criminal speeding, speeding in a school zone). Non-speed moving violations are safety-related violations committed while the vehicle was in motion, such as failing to signal when changing lanes, failing to stop, tailgating, or driving too slowly. DUI violations are included in the non-speed moving category. Equipment violations are violations in which a driver's automobile lacks proper equipment, has non-functioning equipment, or has equipment deemed unsafe (e.g., broken taillights or headlights, cracked windshields, illegal modifications, opacity on window tint). License/insurance/registration issue violations are violations associated with licensing (vehicle or driver), insurance, and registration. Examples include driving with a suspended or revoked license or expired registration, failing to possess insurance, and driving without license plates. Stops with ARS 28-3151A violations are categorized separately. Finally, the other violations category includes all violations that cannot be identified as one of the above categories. This category includes a diverse collection of offenses, such as drug violations, seat belt and cell phone violations, parking violations, noise violations, and littering violations. In 2025 (similar to 2024), speed violations were the most common violations, followed by license/insurance/registration issue violations (Figure 8).

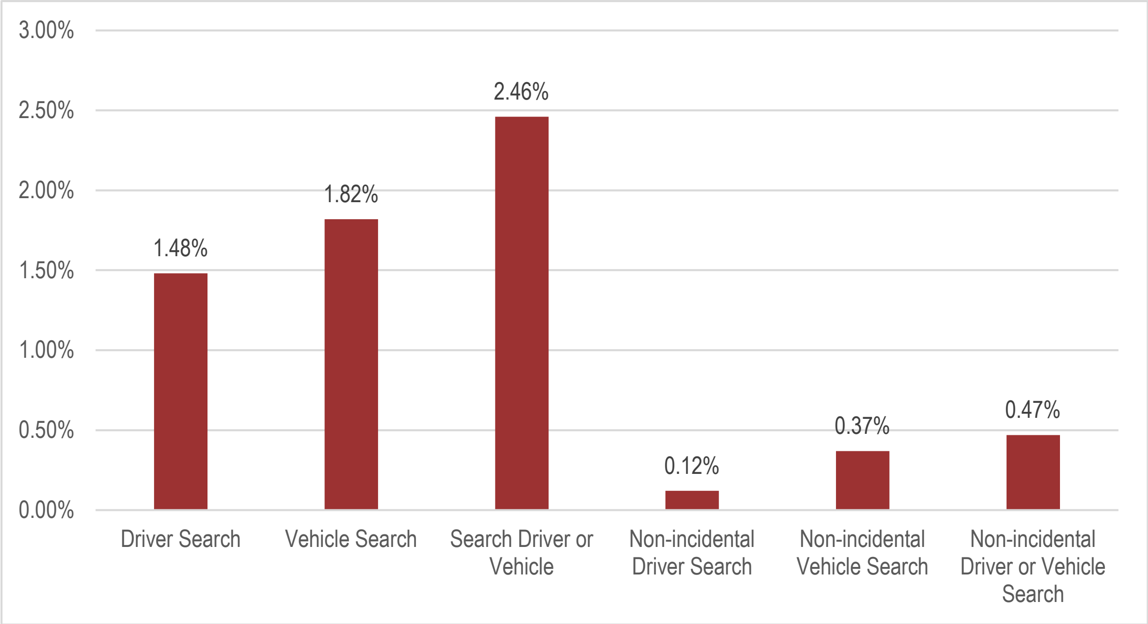
Figure 8. Violation categories



Note: The combined percentages exceed 100 percent because drivers may be cited or warned for more than one offense.

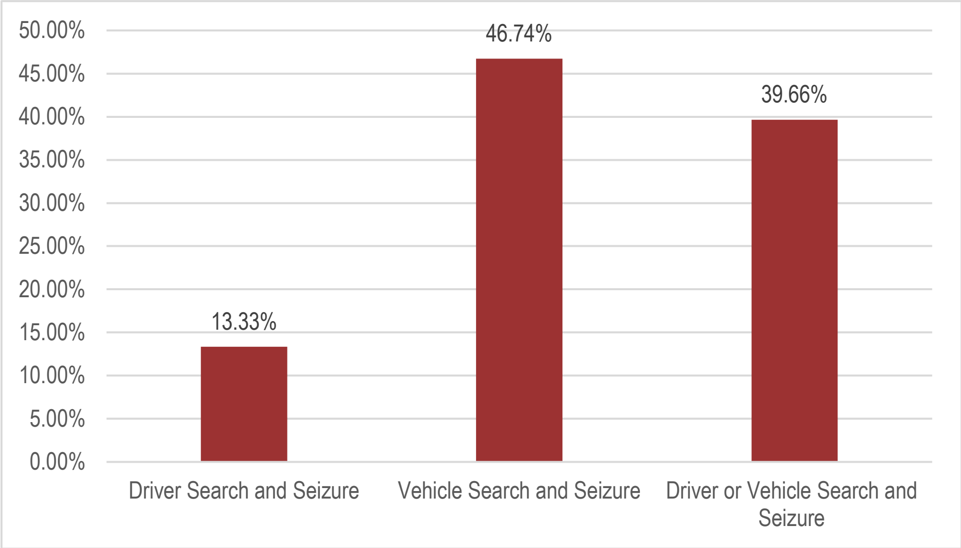
Figure 9 presents information about searches as a percentage of total stops. MCSO policy dictates that deputies search all drivers taken into custody, all drivers given courtesy rides, and all towed vehicles; these searches are not discretionary on the deputy's part. Non-incidental searches are not connected to arrests, courtesy rides, or tows, meaning they are discretionary searches conducted by deputies. Most searches of drivers occurred incident to arrest. Arrests occurred during 6.28 percent of all traffic stops; however, nearly 75 percent of these arrests were cite-and-release rather than custodial arrests. Only 334 searches of drivers were conducted incident to arrest, representing just 1.36 percent of all stops. For the comparative analysis, we considered non-incidental searches of drivers or vehicles as a search outcome; in 2025, MCSO deputies conducted slightly more non-incidental searches of vehicles than of drivers.

Figure 9. Searches



For all stops involving a search, deputies record whether items were seized on the stop in which the search occurred (i.e., "hit rate"). Overall, 39.66 percent of non-incidental searches resulted in seizures (Figure 10).

Figure 10. Seizures during non-incidental searches



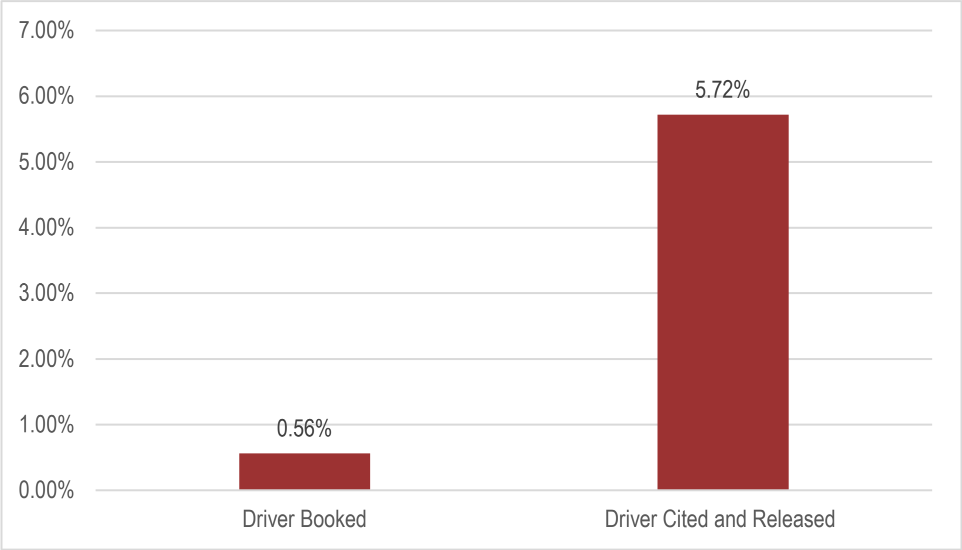
Deputies use the driver arrest variable field to document the type of arrest associated with each traffic stop. Arrests fall into six classifications:

- Booked arrests
- Cite and release, custodial arrest
- Cite and release, no custodial arrest
- Custodial arrest, pending follow-up

- Custodial arrest, no further action
- Custodial arrest, released to other agency

Depending on the circumstances and charges, deputies may exercise discretion in determining the appropriate arrest classification. For example, when arresting a driver for DUI, a deputy may decide the individual is too impaired to be released on their own recognizance or to a sober, licensed driver, so the individual would then be booked. Arrests of drivers remain rare among traffic stops. Cite-and-release arrests without custodial detention account for 74.53 percent of traffic stop arrests, and cite-and-release/no custodial arrest incidents represent 4.68 percent of all traffic stops. Less than 1 percent of stops result in a booked custodial arrest of the driver (see Figure 11).

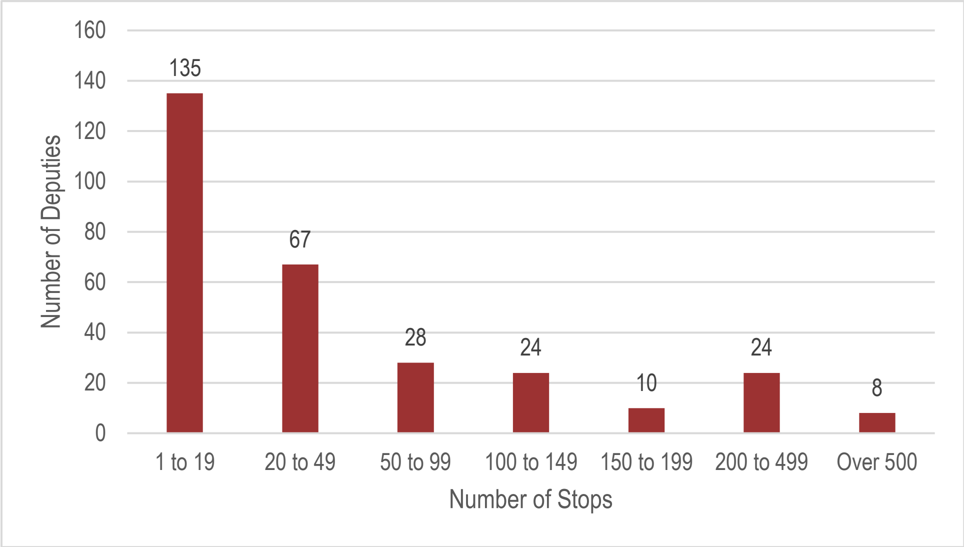
Figure 11. Arrests during traffic stops



Deputy characteristics

The dataset includes traffic stops made by 296 deputies from the MCSO. We present data about deputy traffic stop activity measured as the total number of stops conducted by deputies over the 12-month period in this analysis. As Figure 12 shows, most deputies conducted between 1 and 49 stops during this period, but a few deputies made more than 500 stops in the same period. This finding was similar to the findings in previous annual reports.

Figure 12. Deputy traffic stop count (number of stops over the 12-month period)



Comparative analysis

In this section, we present the findings from analyzing each stop outcome, and we summarize the findings from the propensity score matching statistical analysis. This report also includes the following supplemental appendixes:

- Supplemental Appendix 1 presents descriptive statistics for all variables.
- Supplemental Appendix 2 includes output from the regularization models that created the propensity scores.
- Supplemental Appendix 3 includes detailed tables of the propensity score matching results.
- Supplemental Appendix 4 provides results from the analyses of stop length that include extended stop indicators.
- Supplemental Appendix 5 provides results from all other alternate specifications.
- Supplemental Appendix 6 provides details on the results of the common support and balance tests for our main models.

We present the full analysis of seizures predicated on searches in the main body of the report.

For the propensity score matching results, we used a p-value of 0.05 or less to indicate statistical significance. Given that the sample size for all analyses was more than 100, the critical t-statistic was 1.96 (t-statistics above this value indicate statistical significance, and those below indicate a failure to reject the null hypothesis, or no statistically significant difference).

Common support and balance assumptions were met for all the baseline analyses (see Supplemental Appendix 6 for further details on these tests). In propensity score matching analysis, common support is necessary for valid estimation, meaning that all observations contain a positive probability of being in the condition of interest or not, based on the propensity score (Khandker et al., 2010). Balance evaluates the effectiveness of the matching procedure in reducing observable differences between observations in and out of the condition of interest (Khandker et al., 2010). After matching takes place, the differences between observations in the condition of interest and their matches on the observable characteristics used for matching should be minimal.

Stop length

The analysis team investigated differences in stop length between Hispanic and White drivers, Black and White drivers, and all racial/ethnic minority and White drivers. As noted in the previous section, deputies can indicate whether they experienced specific circumstances that extended the length of a stop beyond their control, including technical issues (e.g., a printer failure), a language barrier, a DUI stop, training, calling for a tow, documentation issues, and other issues. The stop length analyses included all extended stops as matching variables based on MCSO's TSQRs 3, 13, 17, and 21, which audited extended stop length indicators and found that deputies were using them appropriately.

To provide context and a comparison point, the average stop length for White drivers in 2025 was 13.28 minutes (or approximately 13 minutes and 17 seconds), with a standard deviation of 15.39 minutes (or approximately 15 minutes and 23 seconds). Table 4 summarizes the findings from this analysis. **For similarly situated stops, our analysis found no statistically significant differences in stop lengths.**[24] The deprecated specifications found in Appendixes 3 and 4 resulted in slightly different findings. Three models found no statistically significant difference in stop length, but a fourth model identified a statistically significant difference in stop length between Hispanic and White drivers. This model identified a difference between Hispanic and White drivers of 1.84 minutes, using all stops and not controlling for extended stop indicators.

Table 4. Propensity score matching results for stop length, extended stops as matching variables

Model	Difference (in Minutes)	T-statistic	Statistically Significant?
Hispanic vs. White drivers	-1.80	-1.65	No
Black vs. White drivers	0.69	0.71	No
Minority vs. White drivers	-1.10	-1.29	No

Citations

The analysis team investigated differences in citation rates (i.e., the percentage of stops that resulted in citations rather than warnings or incidental contact receipts) between Hispanic and White drivers, Black and White drivers, and all racial/ethnic minority and White drivers. To provide context and a comparison point, 56.88 percent of stops involving White drivers ended in a citation. The analysis included ARS 28-3151A as a matching variable. ARS 28-3151A citations were present in 6.38 percent of stops of Hispanic drivers but in only 0.57 percent of stops of White drivers. Table 5 summarizes the findings from this analysis. **For similarly situated stops, we found a statistically significant difference in citation rates between Hispanic drivers and White drivers, but we found no differences in citation rates between White drivers and the other two groups.** Hispanic drivers received citations at a higher rate (2.70 percentage points higher) compared to White drivers.[25] For deprecated specifications (found in Appendixes 3 and 4), we also identified statistically significant differences in citation rates between Hispanic and White drivers when including special assignments as a matching variable. In this case, the citation rate for Hispanic drivers was 2.37 percentage points higher than the citation rate for White drivers.

[24] Note that the "all racial/ethnic minorities" analysis included Hispanic, Black, Asian, and Native American drivers. Because of the inclusion of additional racial and ethnic groups, these results may differ from those of individual analyses of Hispanic or Black drivers.

[25] This finding represents an odds ratio of 1.1167, meaning an increased chance of Hispanic drivers receiving a citation (when compared to White drivers) of 11.67 percent.

Table 5. Propensity score matching results for citations

Model	Difference (Percentage Points)	T-statistic	Statistically Significant?
Hispanic vs. White drivers	2.70	2.25	Yes
Black vs. White drivers	-3.19	-1.78	No
Minority vs. White drivers	1.16	1.11	No

Searches

The analysis team investigated differences in search rates (i.e., the percentage of stops that involved searches not incident to arrest or tow) between Hispanic and White drivers, Black and White drivers, and all racial/ethnic minority drivers and White drivers. To provide context and a comparison point, 0.32 percent of stops of White drivers involved a non-incidental search. Table 6 summarizes the findings from this analysis. **For similarly situated stops, we found no statistically significant differences in search rates that were not incidental to an arrest or a tow.** For deprecated specifications (found in Appendixes 3 and 4), we similarly identified no statistically significant differences in search rates for any groups.

Table 6. Propensity score matching results for non-incidental searches

Model	Difference (Percentage Points)	T-statistic	Statistically Significant?
Hispanic vs. White drivers	-0.05	-0.21	No
Black vs. White drivers	-0.05	-0.14	No
Minority vs. White drivers	-0.20	-0.91	No

Arrests

The analysis team investigated differences in arrest rates (i.e., the percentage of stops that involved arrests) between Hispanic and White drivers, Black and White drivers, and all racial/ethnic minority drivers and White drivers. To provide context and a comparison point, 4.99 percent of stops involving White drivers ended in an arrest. Table 7 summarizes the findings from this analysis. **We found statistically significant differences in arrest rates across all three comparisons.** For deprecated specifications (found in Appendixes 3 and 4), we found statistically significant differences for Hispanic drivers compared to White drivers when we included special assignments as a matching variable. We also found statistically significant differences for Hispanic drivers compared to White drivers for booked arrests (compared to all stops). Hispanic drivers were arrested at a rate 0.47 percent higher than that for White drivers. Finally, and across all three comparison groups for non-warrant arrests (compared to all stops), White drivers had statistically significant lower arrest rates than the rates of the other groups (Hispanic difference = 2.19 percent; Black difference = 2.96 percent; all racial/ethnic minority difference = 2.63 percent).

Table 7. Propensity score matching results for arrests

Model	Difference (Percentage Points)	T-statistic	Statistically Significant?
Hispanic vs. White drivers	2.61	4.25	Yes
Black vs. White drivers	3.16	3.27	Yes
Minority vs. White drivers	2.58	4.64	Yes

Seizures

The analysis team investigated differences in seizure rates that occurred on stops in which a non-incidental search occurred by the race/ethnicity of the driver. Deputies made 116 stops involving non-incidental searches during the analysis period. Table 8 presents a breakdown of searches with and without seizures by the race/ethnicity of the driver. The chi-square test of homogeneity returned $\chi^2=11.84$, $p=0.02$, and the Fisher's exact test returned $p=0.01$, indicating a **statistically significant difference in the distributions of searches with and without seizures across driver race or ethnicity**. These findings are inconsistent with those of the previous annual reports.

Table 8. Seizures during non-incidental searches by the race/ethnicity of the driver

Race/Ethnicity of the Driver	Number of Searches	Percentage of Searches Without Seizures	Percentage of Searches with Seizures
Asian	2	50.00%	50.00%
Black	18	77.78%	22.22%
Hispanic	41	70.73%	29.27%
Native American	3	100.00%	0.00%
White	52	44.23%	55.77%
Overall	116	60.34%	39.66%

Conclusion

The MCSO and the CNA analysis team **conclude that there is evidence of disparate citation rates, arrest rates, and seizure rates by drivers' race/ethnicity in the 2025 traffic stops in the baseline analysis.** The MCSO is encouraged that there were no statistically significant differences in stop length. For citation rates, we found a statistically significant difference only when comparing all Hispanic drivers to White drivers. Stops involving Black, Hispanic, and all racial/ethnic minority drivers were not more or less likely to result in longer stops or higher search rates. However, in terms of arrest rates, we found statistically significant differences in all comparison groups. For the first time, we identified a statistically significant difference in seizures following searches.

We identified disparities in some stop outcomes. In Table 9, we report the measured difference in benchmark metrics for TSARs conducted since 2017. The calculated differences for each year cannot necessarily be assumed to represent statistically significant changes over time; this information is purely descriptive. The arrest disparity for all racial/ethnic minority drivers was lower than it was in 2024 (as indicated in Table 9), but the difference in arrest rates between White and Hispanic drivers was higher in 2025 than in 2024.[26] Notably, we did not identify statistically significant differences for any group in the baseline analysis for search rates.

[26] Notes on models used for comparisons:

- All models use White drivers as the comparison condition, reflecting the change made for the 2019 analysis.
- All models reflect a correction to the statistical syntax used to classify the time of day and define non-incidental searches of vehicles. The uncorrected syntax was present in the 2017–2018 and 2019 models.
- All models use the matching variables used in the original analysis, and the 2017–2018 analysis includes fewer matching variables (see *Maricopa County Sheriff's Office Traffic Stops Analysis Report: January 2019–December 2019* for details on the added variables).
- All stop length models reflect the analysis with extended stops removed, reflecting the change in the baseline model made for the 2021 analysis. This model is found in Table 7 in previous TSARs.
- All models for the 2022 and 2023 analyses included the introduction of splining certain variables and regularization.
- Models for the 2024 analysis included the use of ARS 28-3151A as a matching variable for the citation outcome. In addition, models for the arrest outcomes removed stop classification as a matching variable for the 2024 analysis.
- Models for the 2025 analysis included the use of extended traffic stop indicators as matching variables for the stop length analyses.

Table 9. Comparison of statistical significance and differences across TSARs[27]

Outcome		Stop length			Citations			Searches			Arrests			Seizures
		Hispanic	Black	Minority	Hispanic	Black	Minority	Hispanic	Black	Minority	Hispanic	Black	Minority	
2017-2018	Diff.	**0.49**	0.35	**0.64**	**3%**	1%	**3%**	**3%**	**2%**	**3%**	**1%**	**1%**	**1%**	**No**
2019	Diff.	**0.91**	**1.28**	**0.94**	**4%**	3%	**4%**	**2%**	**1%**	**1%**	**1%**	1%	**1%**	**No**
2020	Diff.	**1.15**	**1.52**	**0.97**	**4.60%**	0.80%	**3.60%**	**0.90%**	1.10%	**1.00%**	**1.50%**	0.80%	**1.30%**	**No**
2021	Diff.	**0.99**	0.26	0.46	**2.62%**	**-7.27%**	0.98%	**0.67%**	0.53%	**0.46**	**1.31%**	1.13%	**1.45%**	**No**
2022	Diff.	**0.67**	**0.72**	**0.57**	**3.68%**	0.27%	1.03%	**0.65%**	0.25%	0.24%	0.59%	0.77%	0.35%	**No**
2023	Diff.	0.25	0.2	0.25	2.41%	-0.06%	**2.50%**	-0.06%	-0.26%	-0.14%	0.91%	1.54%	0.58%	**No**
2024	Diff.	**0.27**	**0.46**	0.19	2.23%	0.38%	1.50%	0.06%	0.31%	**0.45%**	**2.53%**	**3.19%**	**3.03%**	**No**
2025	Diff.	-1.8	0.69	-1.1	**2.70%**	-3.19%	1.16	-0.05	-0.05	-0.2	**2.61%**	**3.16%**	**2.58%**	**Yes**

Bold numbers represent statistical significance and red numbers indicate an update for the 2025 analysis (TSAR 11)

Note: This table was updated for the 2025 analysis (TSAR 11) to reflect updates to TSAR 8, 9, and 10.

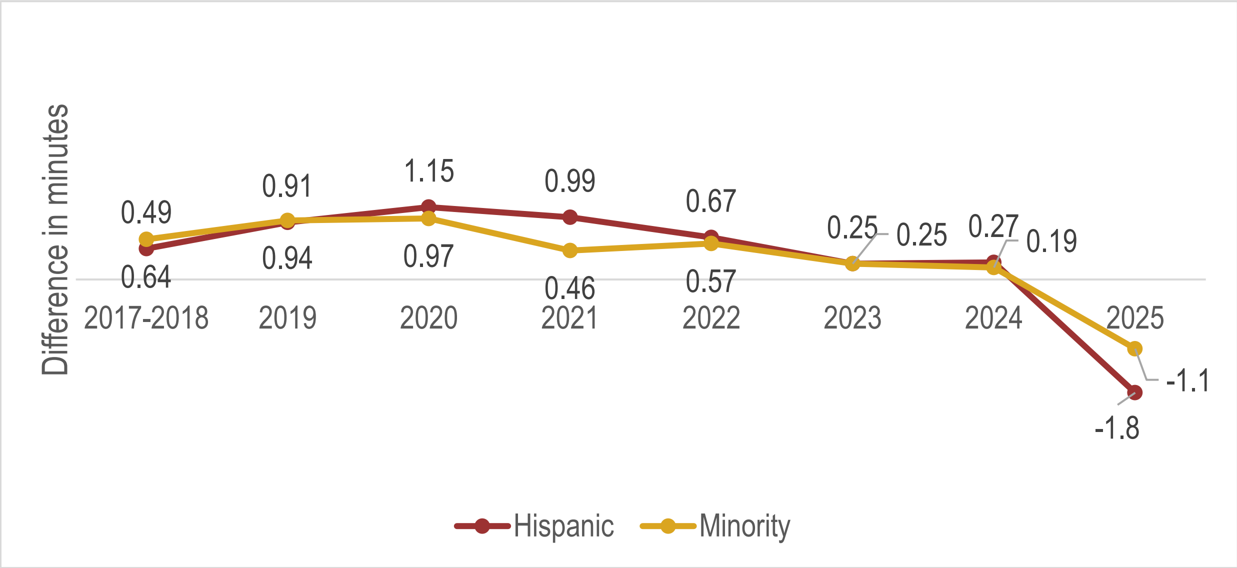
The results of the analyses presented in this report do not indicate that bias exists at MCSO, nor do they directly reflect discriminatory policing. *Biased-free policing*, as defined by the Monitoring Team (Carnevale, 2014), means that "race or Latino ancestry is not a factor in any law enforcement decisions except where allowed by law." An unequal distribution of traffic stop outcomes, as analyzed in this report, may result from a range of external factors outside of individual deputies' control or MCSO policies or practice. Statistical differences in traffic stop outcomes or stop length should not be conflated with bias or interpreted as evidence of discriminatory policing, absent additional evidence demonstrating differential law enforcement action in practice or policy. Per Paragraphs 53, 64, 67, and 69 of the Supplemental Permanent Injunction, inequality identified by analyses conducted by the MCSO are "indicia of possible racial profiling." Per Paragraph 70 of the Supplemental Injunction, the MCSO investigates the findings from these analyses and will take appropriate action if racial profiling exists. Since the MCSO began conducting the TSMR analyses in April 2021, neither the MCSO, the Monitor's team, nor the Parties (the DOJ and ACLU) have identified racial profiling in policy, practice, or the behavior of individuals.

The MCSO remains committed to investigating the cause of all disparate outcomes. MCSO has investigated extended stop indicator use for four data years (2020, 2023, 2024, and 2025); according to the published results of those studies, deputies are using the extended stop indicators appropriately. Through *Traffic Stop Quarterly Report 3: Extended Traffic Stop Indicator Use* and *Traffic Stop Quarterly Report 4: Long Non-Extended Traffic Stops*, the MCSO identified the need to collect additional data regarding stop length because previous TSARs did not account for unmeasured characteristics of stops. In May 2022, the MCSO began capturing delays in traffic stops caused by drivers not having the required driving documentation (i.e., license, registration, and insurance) with them at the time of the stop or caused by drivers taking extra time to find their required documentation. The MCSO also provided an "other" category in which deputies can identify a reason for an extended stop other than those captured by the existing extended stop indicators, which include technical issues (e.g., a printer failure), a language barrier, a DUI stop, training, or a vehicle tow. The MCSO is committed to identifying and documenting the contributing factors to these differences in traffic stop length and is working to mitigate them when possible.

[27] Values reflect reanalysis of 2022, 2023, and 2024 data using adjusted arrest variable as requested by the Monitoring Team at the April 21-23, 2026 site visit.

Figure 13 is purely descriptive; it depicts the difference in the average length of traffic stops across the last eight TSARs. This year, we see a decline for both Hispanic drivers and all racial/ethnic minority drivers when compared to White drivers. The difference in average stop length for Hispanic drivers was approximately 1 minute and 48 seconds faster than White drivers. For all racial/ethnic minorities, the difference was approximately 1 minute and 6 seconds faster than White drivers. All differences in stop length in the baseline analyses were not statistically significant.

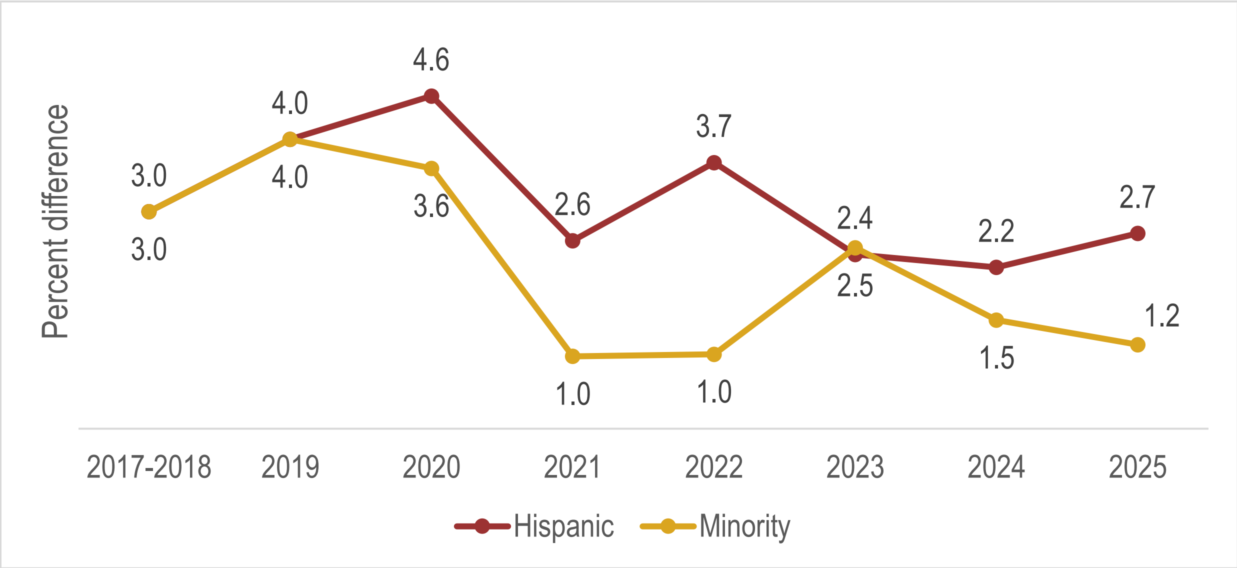
Figure 13. Difference in the average length of traffic stops by race/ethnicity (compared to White drivers)



Note: This graph was updated for the 2025 analysis (TSAR 11) to reflect updates to TSAR 8, 9, and 10.

Figure 14 presents descriptive numbers representing the difference in citation rates for Hispanic drivers compared with White drivers from the last eight TSARs. This difference in citation rates increased for Hispanic drivers from 2024 to 2025, but the difference in citation rates between White and all racial/ethnic minority drivers decreased. The MCSO completed a quarterly report (*Traffic Stop Quarterly Report 6: Citations and Warnings*) analysis to investigate citation disparities and investigated 2024 citation activity in TSQR 19. Examining the types and number of violations that result in citations and warnings helped the MCSO gain insight into the cause of these disparities and therefore understand how to target efforts to combat them. In 2023, MCSO used the offense type of violations as a matching variable for the first time. MCSO continues to investigate citation disparity through the TSMR monthly process.

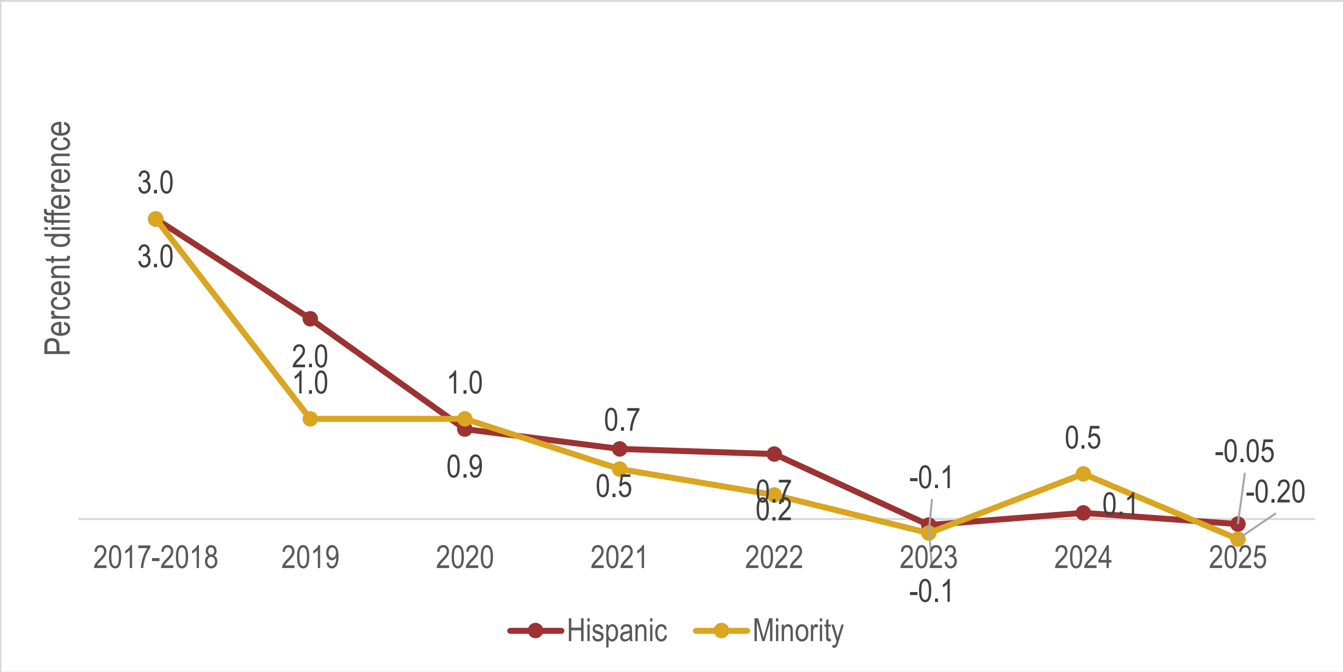
Figure 14. Difference in citation rates by race/ethnicity (compared to White drivers)



Note: This graph was updated for the 2025 analysis (TSAR 11) to reflect updates to TSAR 8, 9, and 10.

Figure 15 shows the difference between search rates for Hispanic and all racial/ethnic minority drivers compared with White drivers from the last eight TSARs. There were no statistically significant differences in search rates.

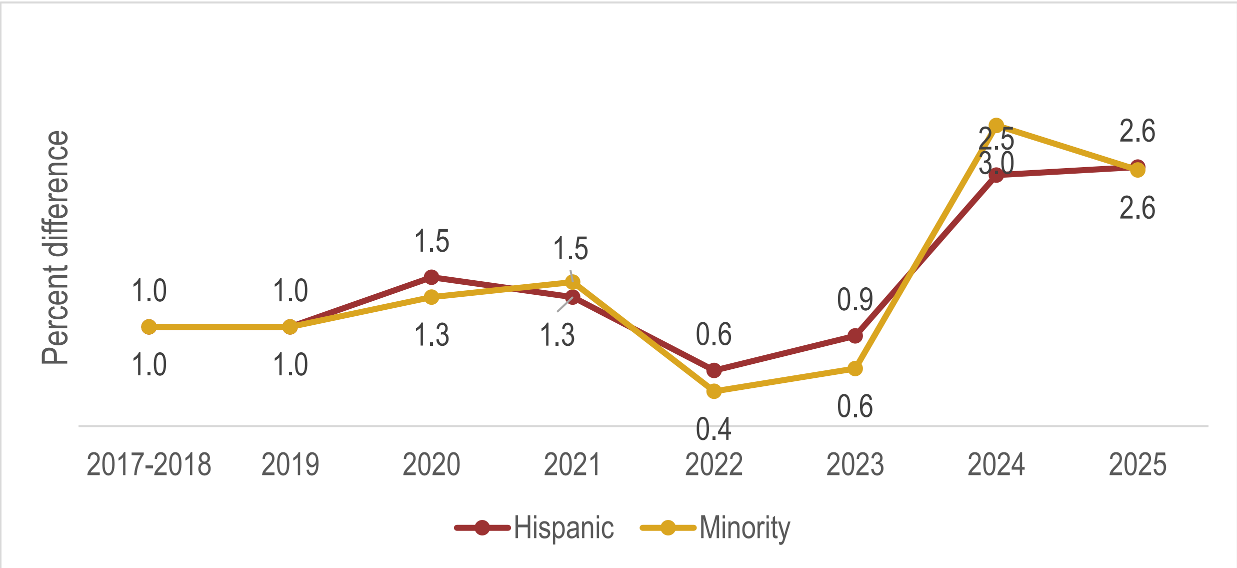
Figure 15. Difference in search rates by race/ethnicity (compared with White drivers)



Note: This graph was updated for the 2025 analysis (TSAR 11) to reflect updates to TSAR 8, 9, and 10.

Figure 16 shows the descriptive trends in arrest rates for Hispanic and all racial/ethnic minority drivers compared with White drivers (based on the last eight TSARs). We see a decrease in arrest rates differences from last year in this TSAR. The MCSO remains concerned about any disparate outcomes and recognizes that these changes stem largely from a change in the methodology beginning in the 2024 TSAR.[28] In addition, MCSO investigated 2024 arrest activity and published results in TSQR 20, and it has a comprehensive understanding of the causes associated with racial and ethnic disparity in arrest rates.

Figure 16. Difference in arrest rates by race/ethnicity (compared with White drivers)



Note: This graph was updated for the 2025 analysis (TSAR 11) to reflect updates to TSAR 8, 9, and 10.

The MCSO is firmly committed to eliminating bias across its operations. *Critical Policy-8: Preventing Racial and Other Bias-Based Profiling* expressly forbids explicit bias. Training on implicit bias has been incorporated into the MCSO's required ongoing training curriculum. In addition, the MCSO has implemented a program to analyze traffic stop data monthly to look for warning signs or indicia of possible bias-based policing or racial profiling. The monthly analysis of traffic stop data is designed to identify disparities between all racial/ethnic minority drivers (i.e., Asian, Black, Hispanic, and Native American) and White drivers for the stop length, citation rate, search rate, seizure rate, and arrest rate benchmarks using both comparative and descriptive analyses. The patrol activity of deputies identified by these analyses is reviewed extensively. This process allows the early identification and monitoring of deputies with identified disparities in outcomes across any of the five benchmarks and provides a mechanism for conducting deputy-level interventions when appropriate.

The MCSO remains vigilant and committed to addressing disparities because they may indicate possible systemic racial bias and because they may negatively affect the community. In the MCSO's patrol function, these disparities may have causes that are not accounted for in this study, including societal systemic bias (which MCSO cannot control). The results of TSQR 6, TSQR 15, TSQR 19, and TSQR 20 identify potential differential offending that is not accounted for in this or previous annual analyses.

[28] In 2024, criminally classified stops were not used as a matching variable for the arrest benchmark for the first time because they were all arrests (and therefore the outcome variable as well).

The MCSO continues to be at the forefront of traffic stop analysis and reporting and has already implemented many nationally recognized and recommended strategies to combat disparities in traffic stops (Council on Policing Reforms & Race, 2023). These strategies include the elimination of performance incentives based on quotas. Deputies receive training in procedural justice, and the MCSO has and continues to deploy a survey for community members who have interacted with its deputies that is designed to capture how well deputies adhere to the principles of procedural justice. The MCSO has implemented and uses its early intervention system to track any disparities identified in deputies' traffic stops, and it conducts interventions when deemed necessary through the TSMR and review process. The MCSO produces several reports each year, including the TSAR and the TSQRs, examining disparities in a continual effort to improve disparate outcomes for the community members it serves. In addition, the MCSO continually evaluates and reviews its policies and procedures. It conducts 21 different audits and inspections and publishes the results to ensure compliance. In addition, the MCSO has implemented training courses over several years designed to improve cultural competencies, educate deputies on explicit and implicit bias, and ensure that bias-based policing does not occur.

Given the cyclical nature of the annual reports (particularly since 2019), many of the actions MCSO has taken in response to the TSARs are meant to address each of the benchmarks. Findings of statistical significance may help the MCSO identify which actions and efforts to prioritize, but the MCSO also strives to continually improve results for each of the benchmarks. In the past two years, the MCSO has developed a process for responding to each of the traffic analysis reports. First, it publishes a report on its website, and it then solicits feedback from internal and external stakeholders. The MCSO command then considers whether to implement this feedback, and the MCSO communicates the results via the traffic stop reports page of the MCSO website. The TSQR 12 was the first study to go through this process. The MCSO is looking forward to continuing this ongoing feedback process with both internal and external stakeholders as these efforts continue.

In response to the findings from last year's TSAR 10, the MCSO conducted the following activities: communicated results to employees and the public through town halls and its website, provided Monitor-approved enhanced training to personnel to address the findings in TSAR 10, developed a real-time information dashboard to help the deputies patrol for traffic safety, developed a traffic stop review dashboard to enable supervisors to review stops conducted by deputies, examined citation rate and arrest disparities, validated the use of extended stop indicators, analyzed disparities both within and between districts, published traffic stop trends on a quarterly basis, and continuously explored data to understand disparities and potential ways to mitigate them. MCSO continues to investigate monthly disparity at the deputy level through the TSMR process, whereby each deputies' traffic stops are analyzed and an investigative review is conducted if statistically significant disparities are identified. None of these reviews have found deputy bias to be the cause of observed disparities.

The information in this report builds upon the MCSO's efforts to implement data-driven approaches to improve the effectiveness and fairness of its traffic patrol activity. The TSAR does not represent all of MCSO efforts to identify and mitigate disparities. Through our quarterly reports, ongoing TSMRs, and reviews of deputy activity, the MCSO is able to identify disparities across these benchmarks that are the result of factors other than bias or discriminatory policing. After reviewing the statistically significant TSMR findings from ongoing research, the Monitor concurred with MCSO that the inequalities in traffic stop outcomes were not associated with bias. Understanding the data and the causes of the traffic stop disparities identified in this report is part of the MCSO's ongoing efforts to identify potential bias, monitor deputy activity, and intervene when necessary.

The MCSO and CNA will continue to work closely to analyze traffic stop activity by MCSO deputies. This work will include developing additional annual analysis reports, monthly analysis reports analyzing individual deputies, and quarterly reports on special topics selected by the MCSO, CNA, and the Monitoring Team, in consultation with the Parties.

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APPENDIX B. ACRONYMS

Acronym	Definition
ARS	Arizona Revised Statutes
ATT	average treatment effect on the treated
DUI	driving under the influence
MCSO	Maricopa County Sheriff's Office
TraCS	Traffic and Criminal Software
TSAR	Traffic Stop Annual Report
TSQR	Traffic Stop Quarterly Report
TSMR	Traffic Stop Monthly Report

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