Estimation of annual average daily traffic (AADT) data for low-volume roads: a systematic literature review and meta-analysis [version 1; peer review: awaiting peer review]

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Abstract

Background: The annual average daily traffic (AADT) data from road segments are critical for roadway projects, especially with the decision-making processes about operations, travel demand, safety-performance evaluation, and maintenance. Regular updates help to determine traffic patterns for decision-making. Unfortunately, the luxury of having permanent recorders on all road segments, especially low-volume roads, is virtually impossible. Consequently, insufficient AADT information is acquired for planning and new developments. A growing number of statistical, mathematical, and machine-learning algorithms have helped estimate AADT data values accurately, to some extent, at both sampled and unsampled locations on low-volume roadways. In some cases, roads with no representative AADT data are resolved with information from roadways with similar traffic patterns.

Methods: This study adopted an integrative approach with a combined systematic literature review (SLR) and meta-analysis (MA) to identify and to evaluate the performance, the sources of error, and possible advantages and disadvantages of the techniques utilized most for estimating AADT data. As a result, an SLR of various peer-reviewed articles and reports was completed to answer four research questions.

Results: The study showed that the most frequent techniques utilized to estimate AADT data on low-volume roadways were regression, artificial neural-network techniques, travel-demand models, the traditional factor approach, and spatial interpolation techniques. These AADT data-estimating methods' performance was subjected to meta-analysis. Three studies were completed: R squared, root means square error, and mean absolute percentage error. The meta-analysis results indicated a mixed summary effect: 1. all studies were equal; 2.
all studies were not comparable. However, the integrated qualitative and quantitative approach indicated that spatial-interpolation (Kriging) methods outperformed the others.

**Conclusions:** Spatial-interpolation methods may be selected over others to generate accurate AADT data by practitioners at all levels for decision making. Besides, the resulting cross-validation statistics give statistics like the other methods' performance measures.

**Keywords**
AADT, Low-Volume Roads, Rural Roadways, Estimating Techniques, Meta-Analysis
Introduction

In 1994, Zegeer et al., documented that the United States had about 3,082,001 miles of two-lane rural roads (Zegeer et al., 1994). Apronti et al. (2016) and Tsapakis et al. (2016) asserted that an estimated 69% of road miles in the United States of America are urban/local and low-volume roads. The manual on uniform traffic control devices (MUTCD) defined low-volume roads as lying outside the built-up areas of cities, towns, and communities. The annual average daily traffic (AADT) for low-volume roads was generally approximated as 400 vehicles per day (Apronti et al., 2016). The Pennsylvania Department of Transportation (PennDOT) defined low-volume roads as having a maximum of 500 vehicles per day (PA Act 89 of 2013; PennDOT, 2014). The 2019 American Association of State Highway and Transportation Officials (AASHTO) guidelines for low-volume roads’ geometric designs further outlined the classifications for low-volume roads. Low-volume roads are for movement and commerce in areas that are classified as ‘local’ for the regional transit areas (AASHTO, 2019).

Transportation engineers at the federal, state, and local levels are familiar with the importance of the AADT dataset (Sharma et al., 2001). From the AADT data, roadway utilization is inferred; the planning and prioritizing is done for the needed and appropriate roadway improvements; and there is a source of information for planning new road-construction projects. Additionally, AADT data are utilized to assist with the development and implementation of traffic-control mechanisms and devices (managing congestion and ensuring safety); to serve as the basis for designing the roadways’ pavements and geometry; to compare characteristics of road sections; to measure the development of land in the affected areas; a measure of air-quality compliance; to function as a means of validating travel modes; and to assist the process for decision making (Park, 2004; Shamo et al., 2015; Sun & Das, 2015; Zhao & Chung, 2001). Therefore, transportation agencies commit a significant portion of their resources (finances and personnel) to various traffic-data collection programs. It is practically impossible to collect complete and extensive traffic data due to the associated cost (Zhao & Chung, 2001). However, an accurate determination or estimation of traffic volumes is important (Sun & Das, 2015; Sun & Das, 2019).

According to Albright (1991), traffic data collection and management have evolved since the 1930s. Summary statistics for traffic volumes served as an introductory AADT process for the transportation profession. In the 1930s, extensive manual-count activities characterized the AADT data collection. However, the mechanical measurement of traffic data was introduced in the 1940s. In the 1950s and 1960s, theoretical directions for annual traffic-summary statistics and calculations were provided. Occasionally, some uncertainties were encountered with the procedures, and until the late 1980s, the process was not challenged (Albright, 1991). Because the process was the only basis, reports were produced on the status of the roadways’ traffic. Fekpe et al. (2004) and Tsapakis et al. (2016) noted that there are no universal methods to calculate the adjustment factors for the collected traffic data. Therefore, most states rely on the traffic management guide (TMG) to achieve corrected data. The transportation department uses its discretion to select sampling and AADT estimation techniques. Estimates of roadways with similar characteristics are used when it is impossible to access some road segments to conduct a traffic count.

Because there are fewer vehicles per day for the average daily traffic (ADT), Sharma et al. (2001) state that it may not be feasible to install automatic traffic recorders (ATR) for collecting continuous traffic data at set time intervals on low-volume roadways. These isolated locations with ATRs may not be reliable to determine AADTs. Furthermore, some ATRs may break down or become faulty, and they may need time to be fixed or replaced. As a result, vital data for the documentation and determination of AADT on the roadways may be lost. On low-volume roads, data-collection processes may be impeded by the high expense and time constraints (Apronti et al., 2016; Tsapakis et al., 2016). Due to scarce resources (human, capital, and equipment), it is uneconomical to collect consistent and systematic traffic data about low-volume roads.

The methods used to collect AADT data for low-volume roads involve counting traffic with a hand tally and/or video recording for two consecutive hours between 3 pm and 6 pm, or via automated traffic counter for either a period of two or 24 hours (PennDOT, 2014). Regardless of the vehicle’s type and direction at the selected road segment, the vehicle is counted (PennDOT, 2014). Data-collection activities are completed to avoid seasonal activities (fluctuations) or circumstances that may lead to an artificially low average daily traffic count. Seasonal times may include summer recess periods for schools and temporarily or partially restricted road-segment areas (PennDOT, 2014).

Other methods for AADT data collection are non-traffic count-based and travel-demand models. The non-traffic count-based and travel-demand models use data such as socioeconomics, the census, land uses, road networks, and temporal variables (Tsapakis et al., 2016). Furthermore, existing traffic count data may be validated or extrapolated to estimate AADT data. Although travel-demand models are used to estimate AADT for low-volume roads, the development and implementation cost compared to non-traditional models is high (Tsapakis et al., 2016). In addition, travel-demand models are more challenging to implement than regression models (Tsapakis et al., 2016). Much time is needed to create a transportation-analysis zone, which, likewise, requires information about the theory behind the travel-demand model’s implementation and calibration for large rural areas (Tsapakis et al., 2016).

Wang and Tsai (2013) emphasized that not much has been done about cost-effective data-collection plans. Therefore, Wang and Tsai (2013) recognized the need for finding cost-effective techniques for AADT data estimation, reducing data-collection locations, and maintaining data accuracy with a constrained budget. Despite the high costs associated with traffic-data collection, over-dependence on some of these datasets may be misleading, thus resulting in imprecise AADT data estimates, which affects the ultimate goal of planning and development.
Therefore, Tsapakis and Schneider (2015) suggested an integrated data-collection and estimation approach to achieve the desired accuracy.

Researchers in academia and some transportation officials have committed to techniques that ensure that the AADT data obtained for low-volume roads are accurate. For example, regression models and existing counts may accurately estimate an uncounted segment. The process also utilizes socio-economic data, network connectivity, and other information that is needed to predict AADT (Tsapakis et al., 2016). For example, suppose an uncounted segment falls within a group of roads with similar characteristics. In that case, the AADT values for these roads are used for the uncounted segments (Tsapakis et al., 2016).

Researchers utilized regression methods to estimate some road segments in Alabama, Florida, Indiana, Kentucky, Minnesota, and Wyoming (Apronti et al., 2016; Cheng, 1992; Deacon et al., 1987; Lu et al., 2007; Mohamad et al., 1998; Raja et al., 2018; Shon, 1989; Xia et al., 1999). Others adopted logistic-regression methods (Apronti et al., 2016), artificial neural networks (Sharma et al., 2001), a traditional factor approach (Sharma et al., 2000), the smoothly clipped absolute deviation (SCAD) penalty (Yang et al., 2011; Yang et al., 2014), geographically weighted regression (GWR) (Zhao & Park, 2004), Support Vector Regression (SVR) (Castro-Neto et al., 2009) geographical information system-based travel demand models (Zhong & Hanson, 2009), satellite imagery (Yang et al., 2014), and spatial interpolation (Shamo et al., 2015). Eom et al. (2006) considered spatial trends and spatial-correlation (geostatistical Kriging) methods for AADT estimates. A review conducted by Tsapakis et al. (2016) suggested substantial differences in the structure for these methods when estimating AADT on low-volume roads. The authors noted the differences with the techniques and error levels that resulted from data inaccuracies and input.

Staats (2016) also identified problems associated with several AADT estimating methods. For example, in the author’s assertion, none of the methods could be directly applied to estimate the AADT on local roads in Kentucky. As a result, the models were modified before use, or new models, which were suitable for the purpose, had to be built. Therefore, Staats (2016) concluded that the models were created with conditions and characteristics to fit the areas for which they were developed. In addition, all the identified and documented estimating techniques asserted different levels of accuracy for AADTs that were determined or predicted at different locations (Park, 2004).

Further, some models (travel-demand models) were biased toward major roads and omitted most minor road networks (Tsapakis et al., 2016). Therefore, although Staats (2016) suggested that these methods are acceptable for estimating AADT, some cautions and restrictions were advised. Otherwise, the resulting output may be associated with errors ranging from low to very high levels.

Tsapakis et al. (2016) suggested that these errors result when some estimators utilize adjustment factors from high-functional roads in low-volume road areas. These road types are expressively dissimilar in terms of characteristics and travel patterns when used for the estimating processes. In addition, low-volume roadways are homogenous compared to higher-classified roadways. As a result, the AADT values for low-volume roads are skewed due to high-count outliers (Wang & Kockelman, 2009). However, it is worth noting that models that are suitable for groups of counted roads which have similar features may be adopted for groups of uncounted roads (Tsapakis et al., 2016). The disadvantage is the increased complexity, computing assumptions, and the needed knowledge about the statistical processes for non-traffic data (Tsapakis et al., 2016). Some issues that limit the estimates’ accuracy are the complications associated with segmenting roadways, the overwhelming experience required for data collection and the use of these estimating techniques, the process of inputting data from the several influencing factors for traditional methods, and the nonexistence of or inadequate AADT data (Tsapakis et al., 2016).

However, Park (2004) contended that some methods could not explain the influence of the independent variables’ spatial variability on the dependent variables. However, geostatistics interpolate values at unmonitored geo-spaces of interest (Kethireddy et al., 2014). Eom et al. (2006) and Wang and Kockelman (2009) indicated that Kriging is a better option for spatial extrapolation and the prediction of AADT when based on the points' nearest sampling site. Wang and Kockelman (2009) proposed using the Kriging techniques to make better predictions for decisions on pavement conditions, traffic speeds, population densities, land values, household incomes, and trip-generation rates.

The Federal Highway Administration (FHWA) (2015) strategic plan of anticipated improvements for traffic records (21st Century Act-MAP-21 and Fixing America’s Surface Transportation Act [FAST Act]) requires the departments of transportation (DOTs) to report AADT data from all levels or functional classes of roadways within a state to the United States Department of Transportation. We intend to investigate and to select the best AADT estimating technique in order to support the agenda for this strategic plan. The best predictive method(s) is(are) intended to establish and to produce useful reports about low-volume roads while addressing the following issues: cost-effectiveness; time constraints; fewer staff requirements; reducing the difficulty with data input, least error(s); and unrestricted applicability. Also, the predictive model will combine local and global trends as well as spatial correlation and will be able to generate optimized data-collection locations from the model’s output. The combined systematic literature review (SLR) and meta-analysis (MA) approach was utilized to document a list of peer-reviewed articles about estimating AADT for low-volume roads. The articles were quantitatively and qualitatively analyzed. Each AADT estimating methods’ performance was considered and meta-analyzed in order to generate forest plots for the best method.

**Methods**

A combined SLR and MA were utilized for this study.
The SLR enabled the compilation of several published techniques that researchers used to estimate the annual average daily traffic (AADT) for low-volume roadways. Emphasis was placed on low-volume, local, and rural roads. In recent times, several researchers in different fields of study have utilized the combined SLR and MA approach to make inferences and to make better decisions. For example, Adebowale and Agumba (2021) adopted the combined SLR and meta-data analysis approach to investigate challenges undermining labor productivity growth in construction. Their findings resulted in workers’ skills, inadequate training, rework, management style, and incentive to labor as the significant factors impacting construction labor productivity negatively. “To review trends of evolution, pinpoint strengths and gaps in the literature, and identify potential future directions for decision-making research in highway construction projects,” to do away with subjective decision-making processes, a systematic review was conducted by Radzi et al. (2021) using systematic reviews and meta-analysis technique. According to Radzi et al. (2021), their reach finding shows four areas: feasibility, conceptual, detailed scope, and detailed design as existing decision-making tools in improving targets in highway construction projects.

Furthermore, Pansare et al. (2021) used a systematic literature review and analysis of RMS-related research papers from 1999 to 2020. In their research, Neale and Gurmu (2021) and Chellappa et al. (2021) adopted the systematic review of the literature approach. In addition, Neale and Gurmu (2021) investigated the impacts of production pressures in the building sector and proposed mitigation strategies accordingly. In contrast, in India, Chellappa et al. (2021) investigated construction workers’ health and safety using a science mapping approach. Finally, Edwards et al. (2021) performed “a systematic review of the extant literature on the application of driverless technologies in civil engineering.”

In this study, the systematic literature review attempted “to identify, appraise, and synthesize all the empirical evidence that meets pre-specified eligibility criteria to answer a given research question” (The Cochrane Library, 2013). The research was designed to complete the procedures proposed by Membah and Asa (2015), Hong et al. (2012), and Chan et al. (2020). The research articles were found using Boolean operators (AND, OR, and NOT), truncation (* and - symbols), and wildcards (a different word with similar meaning). Peer-reviewed journals, conference publications, technical reports, theses, and dissertations helped to critically conceptualize the concepts discussed in this study. The content analysis of publications about estimating the articles’ methods was based on Tsai and Wen’s (2005) publication. The critical review of the selected publications was based on Yi and Chan (2014). Finally, the quality assessment, data collection, and analysis were completed by adopting Kitchenham et al.’s (2009) processes.

The search procedure started with an all-inclusive search of the available, authoritative electronic databases. These databases included the American Society of Civil Engineering (ASCE); Transportation Research International Documentation (TRID, Transportation Research Board); Scopus; the Web of Science (WoS); and other sources through Yahoo, Google, and Google Scholar. A total of 370 articles associated with AADT were retrieved from these databases. The selected publications reviewed for this research were published between 1999 and 2020. Other articles falling outside of the years (1999–2020) also presented relevant information to guide the write-up. This vital information in the publications outside the stated period was only used to help emphasize the objectives or to introduce the research question. The articles were also selected by the source journal, the methods of AADT estimation used for low-volume roads in the publication, and the number of times a method has been used to explicitly answer the question of estimating AADT on low-volume and rural roads. The selected articles mainly concentrated on single or multiple AADT estimation techniques. The numerous AADT estimation techniques allowed for comparing the performance methods for low-volume and rural roads or for local roads. The final characterization of the publications was based on 19 articles (Table 1) directly related to the estimation of AADT and the evaluation methods for the low-volume and rural roads or the local roads. Figure 1 shows the flow of events for the systematic literature search. The collected articles were analyzed qualitatively and quantitatively to establish the number of techniques available for the low-volume rural or local roads’ AADT estimation.

Several questions based on the analysis of the level of performance of each method employed and the adequacy of information in resolving the AADT estimates in the articles reviewed helped generate the understanding of the concepts and factors that affect the AADT estimation for low-volume roads. In addition, of interest and to better understand the processes, the following research areas were addressed with four compact questions:

1. What are the methods used for estimating AADT on low-volume roads?
2. What methods have been used most to estimate AADT on low-volume roads?
3. What are the shortcomings with the estimation techniques for AADT on low-volume roads?
4. What are the advantages and disadvantages of the estimation methods used on low-volume roads?

Meta-analyzing results from the 19 articles helped in selecting the AADT estimating methods. Kossmeier et al. (2020) adopted a combined meta-analysis and systematic reviews for their research. Schriger et al. (2010), Neyeloff et al. (2012), Liu et al. (2016), Li et al. (2020), and Tamilmanil et al. (2020) completed their studies using meta-analyses to understand the performance of the methods they explored. According to Li et al. (2020), “systematic literature reviews and meta-analysis are increasingly being used to summarize available evidence, develop guidelines, aid in decision-making, and direct future research.” According to Neyeloff et al. (2012), a meta-analysis is essential to synthesize data from primary research. Simultaneously, the forest plot is a graphical
### Table 1. List of articles reviewed for AADT estimation methods associated with local, low volume, and rural roads.

<table>
<thead>
<tr>
<th>Author(s)/ Year</th>
<th>Title of Paper</th>
<th>Method used</th>
<th>Journal/Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raja et al. (2018)</td>
<td>Estimation of Average Daily Traffic on Low-Volume Roads in Alabama</td>
<td>Linear Regression, Known AADTs, And Collection of Socio-Economic and Location Variables</td>
<td>Transportation Research Board 97th Annual Meeting, Washington DC, United States</td>
</tr>
<tr>
<td>Zhong &amp; Hanson (2009)</td>
<td>GIS-Based Travel Demand Modeling for Estimating Traffic on Low-Class Roads</td>
<td>Geographical Information System-based Travel Demand Models</td>
<td>Transportation Planning and Technology, 32:5, 423-439, DOI: 10.1080/03081060903257053</td>
</tr>
<tr>
<td>Yang et al. (2011)</td>
<td>Efficient Local AADT Estimation via SCAD Variable Selection Based on Regression Models</td>
<td>Smoothly Clipped Absolute Deviation Penalty (SCAD) Variable Selection Based on Regression</td>
<td>Chinese Control and Decision Conference, IEEE Transactions on Intelligent Transportation System</td>
</tr>
<tr>
<td>Pan (2008)</td>
<td>Assignment of Estimated Average Annual Daily Traffic Volumes on All Roads in Florida</td>
<td>Linear Regression and Social Economy</td>
<td>Graduate Theses and Dissertations</td>
</tr>
<tr>
<td>Xia et al. (1999)</td>
<td>Estimation of Annual Average Daily Traffic for Nonstate Roads in a Florida County</td>
<td>Multiple Regression Model, GIS</td>
<td>Transportation Research Record: Journal of the Transportation Research Board, <a href="https://doi.org/10.3141/1660-05">https://doi.org/10.3141/1660-05</a></td>
</tr>
<tr>
<td>Author(s)/ Year</td>
<td>Title of Paper</td>
<td>Method used</td>
<td>Journal/Source</td>
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</table>
representation of the systematic and meta-analysis output (Li et al., 2020). The forest plot makes it easier to view variations with different study results. The graphical representation shows the effect estimates and the confidence intervals. After reviewing the papers, the estimation methods were grouped into three categories based on their performance measures. These performance measures were methods of R squared ($R^2$), root means square error (RMSE), and mean absolute percentage error (MAPE). Because some performance measures differed and departed from these three, not all estimation methods could be placed in these three groups. Thus, the individual means to measure performance were not evaluated in the meta-analysis and the subsequent forest plots.

Each of the groups’ analysis was completed based on the stated hypothesis: the null hypothesis assumed that all studies were equal. In contrast, the alternative hypothesis assumed that all studies were not equal or not of the same effect. To examine the null hypothesis that all studies evaluated the same effect may not be possible. Therefore, it was necessary to combine and to consider the heterogeneity of these test results with qualitative assessment studies in a systematic review. However, the summary effect was analyzed on fixed and random-effect models in order to test for the studies’ homogeneity and heterogeneity. The fixed effect assumed that the parameter population and the effect size are the same, wherein assessments were considered to have been conducted under similar settings. Therefore, the error in the sampling process was attributed to the differences in studies. However, the random-effect samples assumed that the sample population can differ (Neyeloff et al., 2012). The decision to use either a random effect or a fixed effect was dependent on the critical values associated with the number of degrees of freedom in the chi-square distribution when compared with the classical measure of heterogeneity (Cochran’s Q). According to

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**Figure 1. Flow chart of the systematic literature review process.**
Gavaghan et al. (2000), when the number of studies was small, Q had a low power as a comprehensive heterogeneity test. In contrast, Higgins et al. (2003) asserted that Q has too much power to test heterogeneity if the number of studies is large. Besides, each of the studies' mean effect in comparison was different and varied with the population. Because the literature search was a product of various studies, different evaluation paths and effects were analyzed with the search. In a study with nonsimilar means from a universe of population, Neycillof et al. (2012) recommended using the random-effect model to enable meta-analysis for a dataset. It was assumed that the sampling error and the population effect contributed to the variability. According to Higgins and Thompson (2002), the percentage of variation across studies due to heterogeneity is described using the P statistic. The inconsistency with the studies’ results is expressed with an intuitive P. P = 100% × (Q-df)/Q. P contrasting Q does not characteristically depend upon the number of studies considered. The forest plots depict the results as a universal path of measures.

Results
This subsection discusses the results of the systematic literature review and the meta-analysis. 300 papers were initially downloaded from ASCE (51), TRID (38), SCOPUS (85), and WOS (126). 70 others were obtained from Yahoo, Google, and Google Scholar. However, most of these publications were cross-referenced. The resulting articles are based on the methods used when gathering articles from the electronic databases, the research questions, and the measure of model performance. In this section, five steps are developed. The first step is aligned with research question 1. Step 1 is identified and outlined from the 19 articles reviewed the methods used in estimating AADT for low-volume roads. The second step is determined from the listed techniques and their frequency of being mentioned in the journals. Step three looks at the reasons for the shortcomings. The fourth step compiles the reviewed papers and other sources’ advantages and disadvantages for some estimating methods in order to ensure accurate conclusions. Finally, step five assesses the performance measure using meta-analysis and forest plots.

Research question one
What are the methods used for estimating AADT on low-volume roads?
This question is to help describe the techniques used when estimating AADT for low-volume roads. Table 2 provides an example of the summary techniques extracted from various publications. Table 2, therefore, depicts the methods that the 19 articles’ authors identified for AADT estimation on low-volume roads. The sources for the 19 documents are presented in Figure 2. Besides the sources, the number of documents per source is highlighted. Therefore, Figure 2 illustrates the sources and the number of publications.

The Journal of Transportation Research Records had the most with seven articles. Three publications were obtained from conference proceedings. Two publications were found in the Journal of Transportation Engineering and graduate theses and dissertations. The Journal of Geography, the Journal of Traffic and Transportation Engineering, and the International Journal of Statistics and Probability each had one article. Figure 3 displays the number of publications and the years. The most publications about low-volume roads’ AADT, per the inclusion criteria, in a year, were in 2019 (three articles). The years 2001, 2016, and 2018 each had two publications. There were no publications relating to the subject in 2002, 2003, 2004, 2005, 2007, 2010, 2012, and 2015. Besides these dates and the ones mentioned earlier, each year was only associated with a single publication. Although researchers are making efforts, there seems to be much room for more work due to the lack of significant publications.

Research question two
What methods have been used most to estimate AADT on low-volume roads?
This subsection discusses the number of times that a method has been utilized. The methods were tallied using the 19 papers that met the inclusion criteria. Figure 4 displays the number of times, or the frequency, that a technique was counted. Although 19 articles were used in the study, the number of estimating methods was 30. Some authors utilized more than one method to enable comparison. The process showed the shortfalls for the techniques’ performance. From the compiled methodology, the regression methods were utilized the most, a total number of 13 times, thus representing 43.33% of the methods tallied. The artificial neural network (ANN) model was explored three times (10%); smoothly clipped absolute deviation (SCAD), Geographical Information System (GIS), and the travel-demand model were each used twice (7% each).

Table 2. List of AADT estimation methods found in the publications reviewed.

<table>
<thead>
<tr>
<th>AADT estimation methods for low-volume roads</th>
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</thead>
<tbody>
<tr>
<td>Artificial neural networks</td>
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<tr>
<td>Traditional factor approach</td>
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<tr>
<td>Regression methods</td>
</tr>
<tr>
<td>Geographical information system-based</td>
</tr>
<tr>
<td>Smoothly clipped absolute deviation (SCAD) penalty</td>
</tr>
<tr>
<td>Satellite-based Imagery</td>
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<tr>
<td>Travel-demand modeling method</td>
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<tr>
<td>Synthetic minority oversampling technique (SMOTE)</td>
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<tr>
<td>Generalized linear mixed model (GLMM)</td>
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<tr>
<td>Kriging (Geostatistics)</td>
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<tr>
<td>Inverse distance weighting</td>
</tr>
<tr>
<td>Natural neighbor (NN) and trend techniques</td>
</tr>
<tr>
<td>Random Forest</td>
</tr>
</tbody>
</table>
Figure 2. Sources versus the number of publications.

Figure 3. The number of publications versus the year of publication.

Figure 4. Consolidated methods and the number of times they were counted.
The rest of the techniques were employed once. Figure 5 represents the breakdown of the regression method into various types. Support-vector (23%), linear (23%), and multiple (23%) regressions were utilized three times. In contrast, spatial, non-linear, Bayesian, and logistic regressions were used once (about 8% for each technique).

Research questions three and four

What are the shortcomings with the estimation techniques for AADT on low-volume roads?
What are the advantages and disadvantages of the estimation methods used on low-volume roads?

Table 3 is a brief review of the selected articles and illustrates some of the authors’ conclusions. Table 3 also has some factors that influence the AADT estimation accuracy.

This section outlines the advantages and disadvantages for the methods used to estimate AADT on low-volume roads. Analyzing these advantages and disadvantages (examples in Table 4) helps to explain and to comprehend the reasons why researchers have utilized these regression techniques. The easy-to-use and apply regression techniques allow for quick AADT estimates.

PennDOT (2014) notes that, because most counts on low-volume roads are for short intervals, are short-duration counts, and have minimal data points, the regression technique becomes ideal for estimators. The regression technique is utilized most because the other techniques have some bottlenecks to overcome in order to make exploration possible. Therefore, most of the techniques have not been explored much. However, the

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**Table 3. Observations from published papers utilized for qualitative and quantitative analysis, highlighting the importance, shortfalls, and applicability on the various road segments.**

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wang &amp; Kockelman (2009)</td>
<td>AADT values for low-volume roads tend to be skewed due to high-count outliers that result from inadequate data collection in the process.</td>
</tr>
<tr>
<td>Apronti et al. (2016)</td>
<td>Linear-regression methods are prone to errors compared to logistic regression, especially &quot;when there is a need to identify roads impacted by industrial activities for road maintenance scheduling.&quot;</td>
</tr>
<tr>
<td>Raja et al. (2018)</td>
<td>The linear-regression technique used for AADT determination is subjectively completed for low-volume or off-system roads when there is a need to compare and rely on similar roads. Thus, the estimates are probably characterized with errors.</td>
</tr>
<tr>
<td>Wang et al. (2013)</td>
<td>The authors compared the travel-demand modeling method and the regression-based method for AADT estimation and found that the travel-demand method had expressively lower mean absolute percentage errors.</td>
</tr>
<tr>
<td>Khan et al. (2018)</td>
<td>Support-vector regression (SVR), an artificial neural network (ANN), a regression-based model, and a factor-based model were compared to predict AADT by using short-term counts. Support-vector regression (SVR) provided superior and accurate results over all the methods to estimate AADT for the different functional classes of roadways. The errors for estimating AADT were minimal compared to the ANN, regression, and factor-based models.</td>
</tr>
<tr>
<td>Zhao &amp; Chung (2001)</td>
<td>Geographic information system technology and multiple linear regression models were used for low-volume road AADT estimation. The models may not be applicable to other urban areas.</td>
</tr>
</tbody>
</table>

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**Figure 5. Percentages for the most-used regression techniques.**
<table>
<thead>
<tr>
<th>Methods</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local regression using travel demand</td>
<td>Helps to group; highly aggregated; easy in application and use; linear regression of daily short count volumes gives more accurate results than the factoring method.</td>
<td>Requires minimum data points; In theory, a minimum of data points is sufficient to complete linear regression analysis.</td>
</tr>
<tr>
<td>Modified version of a pattern recognition technique known as Support vector regression (SVR); Fuzzy theory and artificial neural network (ANN)</td>
<td>Better results than the traditional sampling Methods; No specific models.</td>
<td>Uses pre-defined aggregated roadway grouping; Leasing models to make machine learning; Non-linear and complicated relationships.</td>
</tr>
<tr>
<td>Clustering and regression trees</td>
<td>Allows more accurate results than the factoring method; Learning with parallel processing power; Makes it more efficient and less complex.</td>
<td>Uses pre-defined aggregated roadway grouping; Leasing models to make machine learning; Non-linear and complicated relationships.</td>
</tr>
<tr>
<td>Traditional Factor Approach</td>
<td>Represents time, persons, and households; time-dependent routing.</td>
<td>Requires several pre-processing steps to improve the model's accuracy.</td>
</tr>
<tr>
<td>Shrime et al. (2020) &amp; others</td>
<td>Analyzing AADT for roadways with similar characteristics.</td>
<td>Ignores the difference among roadways in the same classification group.</td>
</tr>
<tr>
<td>Others</td>
<td>Has better results in forecasting and image processing, and character recognition.</td>
<td>Assumes that the traffic is sampled only once; The accuracy of the factors is reduced when group variability increases; A subjective approach resulting in less-than-ideal average group factors.</td>
</tr>
<tr>
<td>Methods</td>
<td>Advantages / Disadvantages</td>
<td></td>
</tr>
<tr>
<td>-------------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td></td>
</tr>
</tbody>
</table>
| GIS-based (Paramasivam, 2019) | **Advantages:** Highly supportive in all kinds of environments; easy to visualize the spatial information in output maps with groups in different colors, patterns, and clear legends; supportive of all database operations (creation, updating, and manipulation); map accuracy depends on the quality of input data; offers an influential decision-making tool in its administration, policy-making, and instructions; monitoring safety; mapping and surveilling infrastructures; routing; planning; present patterns; interpret spatial correlation targeting potential resources; use for efficient management of resources; for site selection, zoning, planning, and conservation measures; combined GIS and geostatistical technologies incorporated with spatial data and interpolation techniques can be applied to the exploration, assessment, and prediction; integrates spatial and nonspatial data to enable better understanding; refine datasets, data models, and the relation between attributes; allows for existing attributes to be linked with newly defined dataset.  
**Disadvantages:** Expensive; complex setup; training cost; errors in results are due to the frequency of updating of datasets or data models; deals with real-time parameters; overall challenge arising from handling growing datasets; increase with larger-scale data results in geographical errors; data quality directly affects the accuracy; net results are affected by geographic errors; relative loss of resolution; positional accuracy and precision are the functions of the scale of paper or digital map created; any nonspatial data linked to location may also be inaccurate or imprecise; inaccuracies result from mistakes; nonspatial data vary greatly in precision; I privacy violation as is not limited to authorized persons; interpretation is error-prone; failures in initiating or additional effort is required to implement fully; lack of trained persons in the domain and has not been taught to the fullest extent |
| Kriging Methods (Arfaoui & Inoubli, 2013) | **Advantages:** Less error and statistically significant; used to fill-in missing spatial values of satellite-derived data; allows for estimating the unknown; no dependence on the functional classification to estimate AADT effectively, minimal interactive modeling; Standard errors of prediction are more accurate; Spatial and nonspatial variability of random variables can be studied; the determination of the weights is based on the unbiased and optimality conditions; the unbiased condition shows the exactness of the kriging interpolator; works on both stationary and non-stationary data; kriging is controlled by variance estimation which locates the sector of significant error; the semivariogram explains the relationship and difference between the measured and predicted values with the help of spatial auto-correlation and distance measurement; the techniques enhances the distribution of spatial data; techniques offer convenient management of resources; expert interpretation; model-based approach of these techniques optimizes the accuracy of the obtained result; techniques have the ability to reproduce the trend and provide continuity which allows for precise interpretation.  
**Disadvantages:** Ignores the difference within each roadway classification; it estimates the value for the center of each unmeasured grid cell with prediction assumption; points location may be a problem with sampling distribution being random; requires user proficiency; dataset used in the interpolation process might have errors; Spatial interpolation evaluates physical data in a continuous domain; result depends on data input the correctness |
geostatistics (Kriging) method has proven (in other disciplines) to be accurate with minimal errors compared to the associated errors with the regression methods. The regression methods require significantly more computational resources, which, in turn, is more complicated. The Kriging method requires minimal interactive modeling; standard errors of prediction are more accurate; the random variables’ spatial and nonspatial variability can be studied; the weights are based on the unbiased and optimality conditions, and the terrain has no influence on the output. The techniques can reproduce the trend and provide continuity, allowing for precise interpretation.

Meta-analysis
Table 5, Table 6, and Table 7, together with Figure 6, Figure 7, and Figure 8, characterize the output from these meta-analyses.

The tables depict the resulting analysis while the figures present the pictorial forest plots representing the outcomes. Table 5 shows a summary output for the meta-analysis of AADT estimation methods with $R^2$ as a measure of model performance. Table 5 provides the authors/publication years, methods, sample sizes, model performance measures, standard errors, and confidence intervals (lower and upper). The table also lists the study’s hypothesis and other essential model parameters for the meta-analysis. These parameters explain the value of the heterogeneity test (Q) for the variables and the results’ statistical significance.

Ten studies were evaluated (Table 5). The resulting heterogeneity test for both the fixed-effect and random-effects models suggested a random-effect model for model validation. We failed...
Table 6. Summary of the meta-analyses generated from the AADT estimation methods with MAPE as a measure of performance.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Methods</th>
<th>Sample Size</th>
<th>MAPE %</th>
<th>SE</th>
<th>CI Lower</th>
<th>CI Upper</th>
<th>CD</th>
<th>MAPE</th>
<th>CI Lower</th>
<th>CI Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sfyridis &amp; Agnolucci (2020)</td>
<td>SMLR</td>
<td>19,000</td>
<td>15.69</td>
<td>0.03</td>
<td>15.63</td>
<td>15.75</td>
<td>10</td>
<td>1,569</td>
<td>5.63</td>
<td>3,143.63</td>
</tr>
<tr>
<td>Sfyridis &amp; Agnolucci (2020)</td>
<td>Random Forests (RF)</td>
<td>19,000</td>
<td>14.48</td>
<td>0.03</td>
<td>14.43</td>
<td>14.53</td>
<td>9</td>
<td>1,448</td>
<td>5.41</td>
<td>2,901.41</td>
</tr>
<tr>
<td>Sfyridis &amp; Agnolucci (2020)</td>
<td>SVR</td>
<td>19,000</td>
<td>14.47</td>
<td>0.03</td>
<td>14.42</td>
<td>14.52</td>
<td>8</td>
<td>1,447</td>
<td>5.41</td>
<td>2,899.41</td>
</tr>
<tr>
<td>Pan (2008)</td>
<td>Linear Regression</td>
<td>2</td>
<td>46.79</td>
<td>4.84</td>
<td>37.31</td>
<td>56.27</td>
<td>7</td>
<td>4,679</td>
<td>948.02</td>
<td>10,306.02</td>
</tr>
<tr>
<td>Khan et al. (2018)</td>
<td>SVR</td>
<td>7</td>
<td>12.00</td>
<td>1.31</td>
<td>9.43</td>
<td>14.57</td>
<td>6</td>
<td>1,200</td>
<td>256.62</td>
<td>2,656.62</td>
</tr>
<tr>
<td>Khan et al. (2018)</td>
<td>ANN</td>
<td>7</td>
<td>23.50</td>
<td>1.83</td>
<td>19.91</td>
<td>27.09</td>
<td>5</td>
<td>2,350</td>
<td>359.12</td>
<td>5,059.12</td>
</tr>
<tr>
<td>Khan et al. (2018)</td>
<td>Factor-based model</td>
<td>7</td>
<td>16.40</td>
<td>1.53</td>
<td>13.40</td>
<td>19.40</td>
<td>4</td>
<td>1,640</td>
<td>300.01</td>
<td>3,580.01</td>
</tr>
<tr>
<td>Wang et al. (2013)</td>
<td>TDM (78 counting)</td>
<td>10</td>
<td>52.00</td>
<td>2.28</td>
<td>47.53</td>
<td>56.47</td>
<td>3</td>
<td>5,200</td>
<td>446.95</td>
<td>10,846.95</td>
</tr>
<tr>
<td>Wang et al. (2013)</td>
<td>Regression models</td>
<td>10</td>
<td>211.00</td>
<td>4.59</td>
<td>201.99</td>
<td>220.00</td>
<td>2</td>
<td>21,100</td>
<td>900.32</td>
<td>43,100.32</td>
</tr>
<tr>
<td><strong>Effect Summary</strong></td>
<td></td>
<td></td>
<td><strong>20.00</strong></td>
<td><strong>0.55</strong></td>
<td><strong>18.93</strong></td>
<td><strong>21.08</strong></td>
<td><strong>1</strong></td>
<td><strong>2,000</strong></td>
<td><strong>107.46</strong></td>
<td><strong>4,107.94</strong></td>
</tr>
</tbody>
</table>

SMLR = Standard Multivariate Linear Regression, SVR = Support Vector Regression, ANN = Artificial Neural Network, and TDM = Travel Demand Modeling.

\[ H_0: \text{All studies are equal.} \]
\[ H_1: \text{All studies are not equal.} \]

- \( K \) (Number of studies): 9
- \( df \) (Degrees of freedom): 8
- \( Q \) (Test of heterogeneity): 3383.50
- \( I^2 \) (Quantify heterogeneity): 99.76
- \( es \) (Effect summary: fixed effect): 14.86
- \( SEes \) (Fixed): 0.02
- \( CI \) (Random): 14.83
- \( P-Value \): 0.00

\[ Z-Value = 920.79 \]
\[ Q = 1900.84 \]
\[ I^2 = 99.58 \text{ high heterogeneity} \]
\[ ES (Random) = 20.00 \]
\[ CI (Random) = 18.93 \]
\[ P-Value = 0.00 \]

To reject the study’s null hypothesis with the random-effect model because the critical chi-square value for nine degrees of freedom was more significant than the \( Q \) value. The critical chi-square was at a \( Q \) value of 8.287 for the random-effects model compared to the 16.919 critical chi-square value. The \( Q \) value of 23.90 for the fixed-effect model could not be used because it was more significant than the critical chi-square value. \( I^2 \), quantifying the heterogeneity, had a value of -8.90 with the random-effects model, showing low heterogeneity variability between the studies. With the fixed-effect model, the value was 62.34.
indicating a high variability among the studies. Therefore, confidence intervals (lower and upper) with a broader range for random effects were used.

This corresponds to the random-effect model with a CI between 0.60 and 0.75 instead of the fixed effects of 0.6 to 0.70. The P-value at 0.00 was less the 0.05, making it statistically significant. Figure 6 is the forest plot for Table 4. The plot was generated using Microsoft Excel and followed what was described in Neyeloff et al. (2012). The graph has scatter markers of different colors and shapes, horizontal lines running through the markers, and a vertical line representing the central tendency. The large, black diamond marker corresponds with the study's effect summary.

In contrast, the length of each horizontal line corresponds with the spread of that study's 95% confidence intervals. The horizontal lines are, conceivably, the essential part of the graph. A line crossing the vertical line (line of null effect) indicates no difference in the studies.

In contrast, if the horizontal line does not cross the vertical line, then there is evidence of statistical differences between the evaluated studies. If all horizontal lines cross the vertical line, there is evidence that all of the studies are in agreement. However, the vertical line is the central tendency in the forest plot. Therefore, the proximity of each study's markers to the central tendency gives the agreement associated with the summary effect. Figure 6 illustrates that all evaluated studies agree, thus similar. All markers are also close to the vertical line despite the slight separation for some markers. Khan et al.'s (2018) AADT estimating method is a little widespread from all other studies.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Methods</th>
<th>Events</th>
<th>RMSE (%)</th>
<th>SE</th>
<th>CI Lower</th>
<th>CI Upper</th>
<th>CD</th>
<th>RMSE</th>
<th>CI Lower</th>
<th>CI Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doustmohammadi &amp; Anderson (2019)</td>
<td>Linear Regression</td>
<td>205</td>
<td>32.81</td>
<td>0.40</td>
<td>32.03</td>
<td>33.59</td>
<td>5</td>
<td>3,281</td>
<td>78.41</td>
<td>6,640.41</td>
</tr>
<tr>
<td>Doustmohammadi &amp; Anderson (2019)</td>
<td>Bayesian Regression</td>
<td>205</td>
<td>31.09</td>
<td>0.39</td>
<td>30.33</td>
<td>31.85</td>
<td>4</td>
<td>3,109</td>
<td>76.33</td>
<td>6,294.33</td>
</tr>
<tr>
<td>Apronti et al. (2016)</td>
<td>Linear Regression</td>
<td>13</td>
<td>73.40</td>
<td>2.38</td>
<td>68.74</td>
<td>78.06</td>
<td>3</td>
<td>7,340</td>
<td>465.73</td>
<td>15,145.73</td>
</tr>
<tr>
<td>Apronti et al. (2016)</td>
<td>Logistic Regression</td>
<td>13</td>
<td>83.50</td>
<td>2.53</td>
<td>78.53</td>
<td>88.47</td>
<td>2</td>
<td>8,350</td>
<td>496.74</td>
<td>17,196.74</td>
</tr>
<tr>
<td>Effect Summary</td>
<td></td>
<td></td>
<td>54.54</td>
<td>5.13</td>
<td>44.48</td>
<td>64.61</td>
<td>1</td>
<td>5,454</td>
<td>1006.17</td>
<td>11,914.87</td>
</tr>
</tbody>
</table>

$H_0$: All studies are equal.

$H_1$: All studies are not equal.

$K$ (Number of studies) 4

$df$ (Degrees of freedom) 3

$Q$ (Test of heterogeneity) 710.28

$I^2$ (Quantify heterogeneity) 99.58

$es$ (Effect summary: fixed effect) 33.09

$SEes$ (Random) 5.13

$CI$ (Random) 44.48

$SEes$ (Fixed) 0.28

$Z$-Value 10.63

$P$-Value 0.00

Figure 6 is the forest plot for Table 4. The plot was generated using Microsoft Excel and followed what was described in Neyeloff et al. (2012). The graph has scatter markers of different colors and shapes, horizontal lines running through the markers, and a vertical line representing the central tendency. The large, black diamond marker corresponds with the study's effect summary.

In contrast, the length of each horizontal line corresponds with the spread of that study's 95% confidence intervals. The horizontal lines are, conceivably, the essential part of the graph. A line crossing the vertical line (line of null effect) indicates no difference in the studies.

In contrast, if the horizontal line does not cross the vertical line, then there is evidence of statistical differences between the evaluated studies. If all horizontal lines cross the vertical line, there is evidence that all of the studies are in agreement. However, the vertical line is the central tendency in the forest plot. Therefore, the proximity of each study's markers to the central tendency gives the agreement associated with the summary effect. Figure 6 illustrates that all evaluated studies agree, thus similar. All markers are also close to the vertical line despite the slight separation for some markers. Khan et al.'s (2018) AADT estimating method is a little widespread from all other studies.
Figure 6. Forest plot for the R2 measure of the AADT estimation's performance.

Figure 7. Forest plot for the MAPE measure of the AADT estimation's performance.

Figure 8. Forest plot for the RMSE measure of the AADT estimation's performance.
Similarly, Table 6 and Table 7 display a summary of the meta-analysis for the measure of model performance when using the mean absolute percentage error (MAPE) and root mean square error (RMSE). Nine and four AADT estimating methods, respectively, were meta-analyzed based on the MAPE and RMSE performance measures. In both cases, the evaluation utilized the random-effects model. The studies indicated high heterogeneity for each case when the Q values were compared to the critical chi-square value for the associated degrees of freedom. F values for the two studies were high, indicating high heterogeneity for the studies variability. However, P-values at 0.00 for both outputs indicated statistical significance at a 95% confidence level. Nonetheless, the null hypothesis was rejected in both cases, suggesting that the evaluated studies were not the same. Figure 7 displays the forest plot for the MAPE measure of the AADT estimation’s performance with heterogeneity. All the studies except one were similar to the summary effect. This exception corresponded with Wang et al.’s (2013) regression models. In Figure 8, the forest plot for the RMSE measure of the AADT estimation’s performance depicted high heterogeneity. The studies from the Wang et al. (2013) exhibited similar characteristics. For example, the two studies of Doustmohammadi and Anderson (2019) had similar characteristics. Apronti et al.’s (2016) two studies were also the same. However, both of their studies were plotted on opposite sides of the central tendency.

Discussion
Several estimating techniques evolved after the literature search was conducted. Utilizing the authors’ knowledge in specialty areas, other methods were established. However, further studies are in progress to improve the output. These techniques are believed to bring about dynamics in the industry and help solve estimation precision. The annual average daily traffic (AADT) dataset is required for roadways throughout the United States. Thus, estimation is done at the federal, state, and local levels (Jessberger et al., 2016). Chen et al. (2019) acknowledge the importance of AADT data estimation for traffic engineering. Chen et al. (2019) suggest that AADT data are essential for transportation planning and traffic monitoring and guarantee cost savings to data collection.

Chen et al. (2019) stressed the limitation of allocating automatic traffic recorders (ATRs) to collect AADT data. The ATRs are mostly installed on arterial roads, not local streets or low-volume roads, because of the associated cost. Chen et al. (2019) noted that arterial road capacity is gradually becoming inadequate for the growing traffic demand; thus, local street traffic continues to grow in terms of traffic volumes. As a result, there is a need to predict AADTs for the local streets to avoid skewed and under-representing the services that these road networks deliver. There is no specific convention adopted globally except to modify existing models. However, there is some guidance from the federal highway authority. Nonetheless, Jessberger et al. (2016) asserted the AASHTO’s AADT estimation formula as, typically, the most generally used method. The AASHTO estimation formula can be adopted and used in many circumstances, but not without issues. A characteristic example of a possible issue is the common measurement issue associated with permanent traffic-counting sites where there are missing observations for the hourly traffic volume. An additional limitation with the AASHTO’s AADT estimation formula is the inability to interpret disparities in the numbers of the day of the week in a month or discrepancies in the days of a month (Jessberger et al., 2016). The regression analysis, traditional factor approach/seasonal adjustment factors, travel-demand modeling method, artificial neural networks, cluster analysis, satellite-based imagery, and Kriging, to mention a few, are some models identified. These techniques may be utilized for AADT estimation on low-volume roads. However, there have also been counterarguments about the shortfalls, except under conditions where the techniques are combined.

Consequently, additional validation may be needed to confirm the model’s appropriateness. Staats (2016) affirmed that, in a bid to adopt the ordinary linear regression model developed by Zhao and Chung (2001), which was based on Florida’s road-network conditions, it was only possible to use the model when modifications were made in order to suit the characteristics of Kentucky. The model that was suitable in Florida was not appropriate for direct use on Kentucky’s roads. Notwithstanding, Zhao and Chung’s (2001) models presented R-squared values that ranged from 0.66 to 0.82. Mohamad et al.’s (1998) linear regression model could only be applied to estimate AADT for areas with existing AADT data. Mohamad et al. (1998), when comparing their model to real, existing AADT data, estimated errors from approximately 1.6% to 34.2%. According to Raja et al. (2018), linear-regression techniques were subjective when employed to estimate AADT. Corresponding to Zhao and Park (2004), the geographically weighted regression models accounted for spatial variability in the transportation network. The model generated high R-squared values and minor estimation errors. Utilizing Zhao and Chung’s (2001) data showed that the model outperformed the ordinary linear regression models introduced by Zhao and Chung (2001). Thus, the geographically weighted regression model generally estimates AADT better than ordinary linear regression models.

Furthermore, Apronti et al. (2016) cautioned users about the errors associated with linear-regression methods. However, those authors developed two effectual, cost-effective, and easy-to-use models (linear and logistic regression) to predict traffic volumes for low-volume roads in Wyoming. The linear-regression model gave an R² value of 0.64 and a root mean square error of 72.34%. The logistic-regression model was completed by classifying the road percentages into five thresholds. These thresholds resulted in a correctly classified range from 79% to 88%. Doustmohammadi and Anderson (2019) utilized the Bayesian regression model to generate ADT estimates for low-volume rural and local roads in 12 of Alabama’s counties. Doustmohammadi and Anderson (2019) asserted that linear regression is not always optimal for developing prediction models. Although widely understood, linear regression cannot account for data distribution or the variability of point estimates.
Aside from regression models, artificial neural network (ANN) models, in multiple arrays, have also been explored extensively to estimate AADT (Khan et al., 2018; Sharma et al., 2000; Sharma et al., 2001). The ANN advantage is the capability to model nonlinear correlations. Also, the ANN is not defined by any specific mathematical equation. The ANN’s strengths have been affirmed by Sharma et al. (2000); Sharma et al. (2001), yet Sharma et al. (2001) suggest a percentage error of 25 from the model at an even 95% confidence interval. The travel-demand model is an estimation technique that has been explored with several predictions of future traffic patterns and volumes. The travel-demand model is based on network modeling, trip generation, trip distribution, and trip assignment. Zhong and Hanson (2009) and Wang et al. (2013) explore the travel-demand model on low-volume and local roads. According to Zhong and Hanson (2009), the travel-demand model may be adopted to reduce the cost associated with traffic volume and parameter estimation. The travel-demand model may be used to identify high-volume road segments and funding prioritization. However, Wang et al.’s (2013) travel-demand model has a 52% mean absolute error. The percent mean absolute error from Wang et al.’s (2013) travel demand model seems high; their model performs better than Zhao and Chung’s (2001) ordinary linear regression model. The state of Florida’s turnpike models and the origin-destination centrality-based model are techniques that have been developed and used for AADT estimates. Florida’s turnpike models and the origin-destination centrality-based models rely on several factors that affect AADT. These factors are used as the models’ input to estimate AADT. Florida’s turnpike models require a statewide shapefile, an existing AADT shapefile, employment data, appropriate traffic analysis for the selected zones, and the HERE street network (HERE traffic analytics from HERE technologies use historical road-traffic data). Despite the high R-squared values and the low percent mean absolute error from the origin-destination centrality-based model, the model requires the availability of known AADT data as well as information about the use of the land parcels, the street networks, and the associated boundaries in order to articulate the required prediction. Jessberger et al. (2016) evaluated four estimation methods (simple average; AASHTO; AASHTO with a day of the week or the month-of-year adjustment factors; and Highway Policy Steven Jessberger Battelle- HPSJB) for AADT. In the evaluation, some days did not have all of the hourly observations available. Therefore, the authors had to adjust the weeks’ traffic volume per day and the days per month. However, the authors asserted that there was a remarkable improvement with the accuracy and precision. The comparison was based on the estimations’ bias and precision. Accordingly, Jessberger et al. (2016) successfully evaluated their estimating techniques.

Estimates with geostatistics present the least errors when compared to known, conventional estimating methods (Staats, 2016). The spatial interpolation approach allows for AADT estimates of values for sampled and unsampled locations (Eom et al., 2006; Wang & Kockelman, 2009). Toblers’ first law of geography is the basis for the spatial interpolation (Geostatistics-Kriging) estimation approach. Although extensively explored and successfully used for prediction in other scientific disciplines, geostatistical methods have barely been used in the transportation industry. Eom et al. (2006) explored spatial statistics to estimate AADT on non-free-way facilities. Wang and Kockelman (2009) and Selby and Kockelman (2011) studied spatial interpolation and the universal Kriging model when estimating AADT for Texas roads. Shamo et al. (2015) investigated AADT estimation using linear spatial interpolation. Klatko et al. (2017) utilized Kriging, inverse distance weighting (IDW), natural neighbor (NN), and trending techniques to address the estimation of vehicle miles traveled on local roads. Apronti et al. (2016) suggested using the travel-demand modeling and spatial interpolation methods more accurately when estimating AADT results. The outcome will help compare methods and, at the same time, select an easy-to-implement, cost-effective AADT prediction technique which is best for low-volume roads (Apronti et al., 2016).

Eom et al. (2006) suggested using a geostatistical (Kriging) approach when estimating AADT. Geostatistical models incorporate the spatial dependency of the traffic volume monitored at one station and are correlated with the volumes at neighboring stations. The process allows for the accurate prediction of unknown or unsampled locations. In addition, the process accounts for the spatial trend (mean) and spatial correlation. Eom et al. (2006) proposed that, even with budgetary constraints at all levels of the transportation department, the technique may help to estimate AADT accurately. Wang and Kockelman (2009) noted that pavement conditions, traffic speeds, population densities, land values, household incomes, and trip generation are areas that make up transportation evaluation. Therefore, the application of Kriging techniques may be applied to aid in better decision-making. Wang and Kockelman (2009) encouraged the exploration of Kriging as a better option than other techniques, based on the points closest to the sampling site, for accurate spatial extrapolation and prediction of AADT. Eom et al. (2006) noted that using the geostatistical approach in urban areas has a much better prediction than in rural areas. The assertion was based on data adequacy and availability. However, other literature sources suggested sophisticated geostatistical techniques besides simple Kriging; therefore, data adequacy can be resolved. Thus, spatial interpolation techniques were seen as useful techniques for transportation researchers to obtain accurate estimates. A typical sophisticated geostatistical technique is the empirical Bayesian Kriging (EBK), which can resolve the drawbacks and uncertainties with the datasets’ classical Kriging models. According to Gribov and Krivoruchko (2020), the EBK technique can efficiently interpolate small to large datasets up to a billion data points. Also, EBK can outperform all other predictors with even an ever-increasing complexity in dataset (Gribov & Krivoruchko, 2020).

Limitations and implications
The study is limited to systematically analyzing secondary data related to AADT estimation methods published between 1999 and 2020.
Debates of Transportation decision-makers can adopt the study’s findings to help in selecting appropriate methods for AADT data estimation. This presents an overview of existing research into AADT estimation methods collected from previously published documents. In addition, it provides a valuable suggestion that may be used to validate other methods not included in this document.

Conclusions
Researchers have proven that AADT estimation methods work for the tested locations. Scholars argue that some techniques for AADT estimates have performed better than others. Various authors also claim that several assertions about the AADT data estimation methods could be validated, whereas others cannot be confirmed. Some AADT estimation techniques are only applicable in specific locations. Others require significant data to provide accurate estimates. Several processes to adjust models for a location may be needed for other locations. Some authors discuss techniques that are not applicable at every location of interest. Nordback et al. (2019) caution that certain models serve the purpose of minimizing the errors when estimating AADT for nonmotorized or low-volume roads. Therefore, those models may serve as guides to better the estimation and AADT monitoring programs. 30 AADT estimating methods were obtained by counting methods from each article with the systematic literature review; however, some appeared to have been repeated as some authors compared two or three methods in a single paper. The AADT estimating methods were meta-analyzed based on the measure of performance of the methods. The performance measures utilized were R squared ($R^2$), root mean square error (RMSE), and mean absolute percentage error (MAPE). Forest plots were generated with the results of the meta-analysis. Generally, the results were mixed, indicating a measure of similar effects but under different conditions. Challenges exist when estimating AADT for planning and development, especially when data-collection methods and data acquired are inadequate or are considered rough estimates (Wang & Kockelman, 2009). For example, the reduction-effectiveness ratio method adopted by Wang and Tsai (2013) cannot generate the much-needed cost-effectiveness. The model was intended to reduce data collection, especially in rural areas, on low-volume roads, and in areas with high variability in the dataset. Generally, the authors of the various AADT data estimation techniques aim to generate an accurate and reliable method that all users may adopt for every location. The models were to possibly incorporate spatial and temporal variability and to generate data for unsampled locations. The qualitative evaluation of the advantages and disadvantages in Table 4 places Kriging methods (geostatistical approaches) above all other methods. The result for the Kriging techniques was consistent with generating accurate and precise AADT estimates with fewer errors. Besides, this method is a statistically significant technique. The Kriging methods (geostatistical approach) incorporate both Spatio-temporal variables and unsampled locations in the final outputs and are applied to every location. There are no boundaries and restrictions when using the geostatistical methods. The methods are significantly affected by terrain/ geographical locations, skewness, randomness, and stationarity in the dataset. A stand-alone Kriging method may be preferred to complete the estimation using two or more methods. The normal score transformation to apply the simple Kriging method can approximate non-symmetric data to symmetrical. Recently, the geostatistical approach was proven to be a better option for estimates. The geostatistical approach outperformed many of the methods in use today. Wang and Kockelman (2009) suggested that “Kriging is a promising way to explore spatial relationships across a wide variety of dataset.”

Furthermore, there is an opportunity to produce a much-enhanced form of the Kriging technique. The enhanced geostatistical methods incorporate the ordinary Kriging capabilities while solving additional complexities in the dataset. None of the evaluated techniques were superior to the geostatistics Kriging method. Therefore, the Kriging method may be adapted to generate a universally accepted approach for estimating AADT data values. Other scientific fields, such as environmental research, ore reserve estimation, groundwater quality, health surveys, etc., have successfully employed Kriging geostatistical Kriging methods, such as simple Kriging and other Kriging methods, empirical Bayesian Kriging, geostatistical simulations, and coKriging. These techniques have been confirmed as the potentially preferred methods. These approaches are robust, precise at predicting, and have improved other techniques’ predictive capabilities in practice and applicability. Therefore, the scientific disciplines have confirmed the effectiveness of the geostatistical tools in many publications. To conclude, it is expected that this literature study will serve as a guide for all AADT-data users, especially for local, low-volume, and rural roads, to fill in the gaps and factors that affect AADT estimation when solving with inadequate data-collection and budget issues.

Data availability statement
All data underlying the results are available as part of the article and no additional source data are required.

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