

Article

# Operational Data Integration and Visual Analytics for Decision-Making in SMB Fleets

Ziru Wang <sup>1,\*</sup><sup>1</sup> CAC Auto Group Boston, Natick, USA

\* Correspondence: Ziru Wang, CAC Auto Group Boston, Natick, USA

**Abstract:** This research investigates the integration of operational data and visual analytics to enhance decision-making for small and medium-sized business (SMB) fleets. Effective fleet management is critical for SMBs, impacting costs, efficiency, and customer satisfaction. However, many SMBs lack the resources and expertise to fully leverage their operational data. This study explores how data from various sources, including vehicle telematics, maintenance records, fuel consumption, and driver behavior, can be integrated into a unified platform. We then examine how visual analytics techniques, such as interactive dashboards and geospatial visualizations, can be employed to extract actionable insights. The research focuses on developing a practical framework for SMBs to improve fleet performance, reduce operational costs, and enhance customer service through data-driven decision-making. A case study involving a regional delivery fleet is used to demonstrate the effectiveness of the proposed approach. The implementation led to measurable improvements, including an 8% increase in fuel efficiency (miles per gallon), a 15% reduction in unplanned vehicle downtime, and a 20% decrease in hard-braking incidents. This research provides valuable insights and guidance for SMBs seeking to optimize their fleet operations through data integration and visual analytics.

**Keywords:** operational data integration, visual analytics, fleet management, decision-making, Small and Medium-Sized Businesses (SMBs), telematics, Data-Driven Optimization

## 1. Introduction

### 1.1. Background and Motivation

Small and medium-sized businesses (SMBs) operating fleets face unique challenges in today's competitive landscape. Efficient fleet management is crucial for controlling costs, optimizing resource allocation, and ensuring timely service delivery. However, many SMBs struggle to effectively leverage the vast amounts of operational data generated by their fleets. This data, encompassing vehicle location, fuel consumption, driver behavior, and maintenance records, often resides in disparate systems, hindering comprehensive analysis and informed decision-making [1].

The lack of integrated data prevents SMBs from identifying key performance indicators (KPIs) and understanding the complex relationships between various operational factors. For example, without a unified view of fuel consumption and driver behavior, it becomes difficult to pinpoint inefficiencies and implement targeted training programs. Similarly, fragmented maintenance records can lead to reactive maintenance strategies, resulting in increased downtime and repair costs [2].

Data integration, coupled with visual analytics, offers a powerful solution to these challenges. By consolidating data from various sources into a centralized platform and employing intuitive visualizations, SMBs can gain actionable insights into their fleet operations. This enables them to optimize routes, reduce fuel consumption, improve driver safety, and proactively manage maintenance schedules. Ultimately, the effective

Received: 10 December 2025

Revised: 25 January 2026

Accepted: 07 February 2026

Published: 13 February 2026



**Copyright:** © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

use of data integration and visual analytics empowers SMBs to make data-driven decisions, enhance fleet performance, and achieve a sustainable competitive advantage. The potential benefits include reduced operational costs, increased operational efficiency, and improved customer satisfaction [3].

### *1.2. Research Objectives and Contributions*

This research aims to address the challenges faced by Small and Medium-sized Business (SMB) fleets in leveraging operational data for informed decision-making. The primary objective is to develop a comprehensive framework for data integration and visual analytics tailored to the specific needs and resource constraints of SMB fleets. This framework will encompass methods for collecting, cleaning, and integrating diverse data sources, such as GPS tracking data, fuel consumption records, maintenance logs, and driver behavior metrics [4]. Furthermore, it will incorporate visual analytics techniques to transform raw data into actionable insights, enabling fleet managers to identify areas for improvement in efficiency, safety, and cost reduction.

The key contributions of this study are threefold. First, we propose a practical and scalable methodology for operational data integration in SMB fleets, considering the limitations of existing infrastructure and technical expertise. Second, we present a detailed case study demonstrating the effectiveness of the proposed framework in a real-world SMB fleet environment. This case study demonstrates the tangible impact of data-driven decision-making on core fleet performance areas. Finally, we derive actionable insights and recommendations for SMB fleet managers, providing a roadmap for implementing data integration and visual analytics to optimize fleet operations and enhance overall business performance.

## **2. Literature Review**

### *2.1. Data Integration in Fleet Management*

Data integration is crucial for effective fleet management, enabling informed decision-making based on a holistic view of operations [5]. Existing literature highlights various techniques for consolidating data from disparate sources. These sources commonly include telematics systems providing real-time vehicle location, speed, and driver behavior; fuel consumption data tracked through fuel cards or onboard sensors; maintenance records detailing repairs, servicing, and component replacements; and routing and dispatch systems containing planned routes and delivery schedules. Integrating these diverse data streams presents significant challenges. Data formats often differ, requiring standardization and transformation. Data quality can vary considerably, necessitating cleansing and validation processes. Furthermore, the sheer volume of data generated by modern fleets, represented by a variable  $V$ , demands scalable and efficient integration architectures. The lack of standardized APIs across different vendor systems also complicates the integration process, often requiring custom-built connectors. Successful data integration in fleet management requires careful consideration of these challenges and the selection of appropriate integration techniques, such as ETL (Extract, Transform, Load) processes or data virtualization, to create a unified and reliable data platform [6].

### *2.2. Visual Analytics for Fleet Optimization*

Visual analytics plays a crucial role in transforming raw fleet data into actionable intelligence, enabling informed decision-making for optimization. Various visualization techniques have been employed to represent different aspects of fleet operations. For instance, geospatial visualizations, such as heatmaps and route mapping, effectively illustrate vehicle density, identify congestion hotspots, and optimize delivery routes based on real-time traffic conditions. Scatter plots and time series graphs are used to analyze fuel consumption patterns, identify inefficient driving behaviors, and predict

maintenance needs based on mileage and engine hours. Dashboard interfaces aggregating key performance indicators (KPIs) like average speed, idle time, and fuel efficiency provide a comprehensive overview of fleet performance [7].

However, existing research often focuses on large-scale enterprise fleets, neglecting the specific needs and constraints of Small and Medium-Sized Businesses (SMBs). These SMBs typically operate with limited resources and require cost-effective, user-friendly visual analytics solutions. Furthermore, the complexity of advanced visualization tools can be a barrier to adoption for SMB fleet managers who may lack specialized analytical skills. Therefore, there is a need for tailored visual analytics approaches that address the unique challenges faced by SMB fleets, focusing on simplicity, affordability, and actionable insights derived from readily available data sources like GPS tracking and fuel logs. The effectiveness of a visualization technique  $V$  can be measured by its impact  $I$  on decision-making, considering factors like accuracy  $A$  and timeliness  $T$ :  $I = f(V, A, T)$ .

### 3. Materials and Methods

#### 3.1. Data Acquisition and Preprocessing

The foundation of this research relies on a multi-faceted dataset acquired from several key sources integral to the operation of small and medium-sized business (SMB) fleets. These sources include vehicle telematics systems, maintenance records, fuel consumption logs, and driver behavior monitoring devices [8].

Vehicle telematics data, the cornerstone of our analysis, was obtained directly from the onboard diagnostic (OBD) ports of the vehicles in the participating fleets. This data stream provides real-time information on vehicle location (latitude, longitude), speed ( $v$ ), engine RPM ( $rpm$ ), idle time ( $t_{idle}$ ), and distance traveled ( $d$ ). The data was collected at a frequency of one data point per minute, offering a granular view of vehicle operation.

Maintenance records, crucial for understanding vehicle health and predicting potential failures, were extracted from the fleets' internal management systems. These records detail the date, type, and cost ( $c$ ) of each maintenance event, including both scheduled preventative maintenance and unscheduled repairs. Each record is associated with a specific vehicle identification number (VIN), allowing for integration with the telematics data [9].

Fuel consumption data was gathered from fuel card transactions and manual logs maintained by the fleet managers. This data includes the date, location, and quantity ( $q$ ) of fuel purchased for each vehicle. We calculated fuel efficiency ( $e$ ) in miles per gallon (MPG) by correlating fuel purchase data with distance traveled data from the telematics systems over corresponding time periods.

Driver behavior data was collected through a combination of in-cab monitoring devices and telematics system outputs. This data encompasses instances of harsh braking ( $b$ ), rapid acceleration ( $a$ ), speeding ( $s$ ), and excessive idling ( $t_{idle}$ ). These events were identified using pre-defined thresholds based on industry best practices and adjusted based on the specific characteristics of the vehicles in the study [10].

Prior to analysis, the raw data underwent a rigorous preprocessing phase. This involved cleaning the data to remove inconsistencies, handling missing values through imputation techniques (e.g., mean imputation for short gaps in telematics data), and transforming the data into a consistent format suitable for integration and analysis. Outliers were identified and addressed using statistical methods such as the interquartile range (IQR) method. For analytical and visualization purposes, the minute-level data was then aggregated into daily intervals per vehicle, forming the primary analysis unit (vehicle-day). This aggregation level balances granularity with computational efficiency, and is suited to fleet management decision cycles. Within this vehicle-day unit, key performance indicators (KPIs) were calculated. For instance, miles per gallon (MPG) was computed by dividing the total distance traveled by the total fuel consumed for that vehicle on that day. Metrics related to driver behavior, such as harsh braking events and

excessive idling time, were summed over the same daily window per vehicle. This structured, time-bound aggregation ensures that derived insights and trends are both actionable and comparable [11].

### 3.2. Data Integration Framework

The core of our methodology lies in a robust data integration framework designed to consolidate disparate data sources common in SMB fleet operations. This framework adopts a three-tier architecture: data ingestion, data processing and storage, and data delivery. The data ingestion tier utilizes Apache Kafka to ingest real-time data streams from telematics devices, including GPS coordinates, speed, fuel consumption ( $f$ ), and engine diagnostics. Batch data, such as maintenance records, driver information, and delivery schedules, are ingested through a custom-built ETL (Extract, Transform, Load) pipeline leveraging Python and the Pandas library.

The data processing and storage tier employs a hybrid approach. Real-time data is processed using Apache Spark Streaming for immediate anomaly detection and stored in a time-series database, InfluxDB, optimized for temporal queries. Batch data, along with aggregated real-time data, is stored in a PostgreSQL relational database, chosen for its ACID compliance and support for complex SQL queries. Data quality control is implemented through a series of automated checks within the ETL pipeline and Spark Streaming jobs. These checks include validation against predefined schemas, range checks for numerical data (e.g., ensuring speed  $s$  is within reasonable bounds  $0 < s < s_{\max}$ ), and completeness checks to identify missing values. Data failing these checks are flagged and routed to a separate data quality queue for manual review and correction (Table 1).

**Table 1.** Example of Data Integration Framework Technologies.

Tier	Technology	Purpose	Data Type
Data Ingestion	Apache Kafka (Managed Service)	Real-time data stream ingestion	GPS coordinates, speed, fuel consumption ( $f$ ), engine diagnostics
Data Ingestion	Python/Pandas ETL Pipeline	Batch data ingestion	Maintenance records, driver information, delivery schedules
Data Processing and Storage	Apache Spark Streaming (Managed Service)	Real-time data processing, anomaly detection	Real-time telematics data
Data Processing and Storage	InfluxDB (Managed Service)	Time-series data storage	Real-time telematics data
Data Processing and Storage	PostgreSQL (Managed Service)	Batch and aggregated data storage	Batch data, aggregated telematics data

---

Data Quality Control	ETL Pipeline, Spark Streaming Jobs	Data validation and quality checks (e.g., $0 < s < s_{max}$ )	All data types
----------------------	------------------------------------	---	----------------

---

### 3.3. Visual Analytics Techniques

To facilitate effective decision-making, we employed a range of visual analytics techniques to explore and interpret the integrated fleet data. Our approach centered on creating interactive dashboards that provide a holistic view of key performance indicators (KPIs) related to vehicle utilization, fuel consumption, maintenance schedules, and driver behavior. These dashboards were designed to allow users to drill down into specific data subsets, filter by vehicle type, driver, or time period, and identify trends and anomalies [12].

Geospatial visualizations, utilizing mapping software, were crucial for understanding spatial patterns in fleet operations. We visualized vehicle locations in real-time, tracked routes, and identified areas with high concentrations of activity or frequent stops. This allowed for the optimization of routes, identification of potential bottlenecks, and improved resource allocation. Furthermore, heatmaps were used to represent the density of events, such as speeding incidents or hard braking, across different geographic regions.

Statistical charts, including histograms, scatter plots, and box plots, were used to analyze the distribution of various metrics and identify correlations between different variables. For example, scatter plots were used to examine the relationship between *fuel consumption* and *driving speed*, while box plots were used to compare the *maintenance costs* across different vehicle models. The selection of these visual analytics techniques was driven by their ability to transform raw data into easily understandable visual representations, enabling fleet managers to quickly identify areas for improvement, optimize resource allocation, and make data-driven decisions.

## 4. Results

### 4.1. Fuel Efficiency Analysis

The integrated operational data, combined with visual analytics, provided significant insights into fuel efficiency across the SMB fleet. Initial analysis revealed considerable variance in fuel consumption, measured in miles per gallon (MPG), across different vehicle types and drivers. A scatter plot visualization of MPG against vehicle age immediately highlighted a negative correlation, suggesting older vehicles (age) generally exhibited lower fuel efficiency. Further investigation, using interactive dashboards, allowed us to filter data by vehicle model (model) and engine type (engine). This revealed that certain older models with specific engine configurations were significantly underperforming compared to newer, more fuel-efficient alternatives.

Driver behavior was also identified as a key factor. By integrating GPS data with fuel consumption records, we calculated metrics such as average speed (speed), instances of hard braking (braking), and idle time (idle). Visualizing these metrics against MPG for individual drivers revealed a strong correlation between aggressive driving habits (high speed, frequent braking) and reduced fuel efficiency. For instance, drivers with an average speed exceeding 70 mph consistently showed a 15-20% decrease in MPG compared to those maintaining a more consistent speed. Similarly, excessive idle time, particularly during deliveries, contributed significantly to fuel wastage.

Based on these findings, targeted interventions were implemented, including driver training programs focused on fuel-efficient driving techniques and a phased replacement of older, less efficient vehicles. The visual analytics dashboards were then used to monitor

the impact of these interventions in real-time, allowing for continuous optimization and refinement of fleet management strategies. The results demonstrated a measurable improvement in overall fleet fuel efficiency, with an average increase of 8% in MPG observed within the first quarter after implementation.

4.2. Maintenance Scheduling Optimization

Data integration played a crucial role in consolidating maintenance records, vehicle telematics data (e.g., mileage, engine hours), and parts inventory information into a unified platform. This comprehensive dataset enabled the application of visual analytics techniques to identify patterns and predict potential maintenance needs. Specifically, we employed interactive dashboards to visualize the correlation between vehicle usage ( $x$ ), environmental factors ( $y$ ), and component failure rates ( $z$ ).

The visual analytics platform facilitated the identification of vehicles requiring preventative maintenance based on predicted failure probabilities exceeding a defined threshold ( $p > 0.8$ ). This proactive approach allowed for scheduling maintenance during periods of low vehicle utilization, minimizing operational disruption. Furthermore, the system optimized maintenance schedules by considering parts availability and technician workload, reducing the overall turnaround time for repairs.

The results of the maintenance optimization demonstrated a significant improvement in fleet operational efficiency. We observed a 15% reduction in unscheduled downtime, directly attributed to the proactive maintenance scheduling. This translated to an estimated 10% decrease in maintenance costs, primarily due to reduced emergency repair expenses and optimized parts inventory management. The improved maintenance scheduling also extended the average lifespan of critical vehicle components, contributing to long-term cost savings and improved fleet reliability (Table 2).

Table 2. Impact Assessment of the Predictive Maintenance Framework.

Metric	Definition / Measurement	Analysis Period & Baseline	Result
Unscheduled Downtime	Total duration (in hours) a vehicle is unavailable for service due to unexpected mechanical failure.	3-month post-implementation period compared to the same 3-month period in the preceding year (year-over-year comparison to control for seasonality).	15% Reduction
Maintenance Costs	Total cost comprising parts and labor for unscheduled (emergency) repairs.	3-month post-implementation period compared to the same 3-month period in the preceding year.	10% Decrease

Preventative Maintenance Trigger	A failure probability threshold of $p > 0.8$ generated by the model, above which a preemptive maintenance inspection is scheduled.	–	$p > 0.8$
Vehicle Usage (x)	High-mileage or high-load operational patterns identified as key features in the model.	–	Identified
Environmental Factors (y)	Specific external conditions (e.g., temperature extremes, road type) correlated with component stress.	–	Identified
Component Failure Rates (z)	Key components (e.g., braking system, battery) with the highest predicted failure rates.	–	Identified

Note: The statistical significance of the reductions in downtime and cost was assessed using a paired t-test ( $\alpha = 0.05$ ).

#### 4.3. Driver Behavior Analysis

The integrated operational data, combined with visual analytics, enabled a comprehensive analysis of driver behavior within the SMB fleets. Specifically, we focused on identifying instances of speeding, harsh braking, and rapid acceleration, all indicators of potentially risky driving. Speeding events were flagged by comparing GPS data with speed limits obtained from map APIs. A threshold of 10% above the posted speed limit was used to define a speeding event. The analysis revealed that 15% of drivers exhibited frequent speeding, defined as exceeding the speed limit more than five times per week.

Harsh braking and rapid acceleration were determined using accelerometer data from the telematics devices. Harsh braking was defined as deceleration exceeding  $0.5g$ , while rapid acceleration was defined as acceleration exceeding  $0.4g$ . Visualizations, including scatter plots of acceleration versus time and heatmaps showing the geographic distribution of harsh braking events, allowed for easy identification of problem areas and drivers. We observed a strong correlation between harsh braking events and accident rates, with drivers exhibiting a high frequency of harsh braking being 2.3 times more likely to be involved in an accident. Following the implementation of targeted driver training based on these insights, we observed a 20% reduction in harsh braking events and a 12% reduction in speeding incidents across the fleet within a three-month period.

This demonstrates the effectiveness of data-driven driver behavior analysis in improving overall fleet safety (Table 3).

**Table 3.** Summary Statistics of Risky Driving Events.

Metric	Value
Speeding Event Definition	Exceeding posted speed limit by 10%
Frequent Speeding Drivers	15% of drivers (more than 5 times per week)
Harsh Braking Definition	Deceleration exceeding 0.5g
Rapid Acceleration Definition	Acceleration exceeding 0.4g
Accident Rate Correlation with Harsh Braking	Drivers with high harsh braking frequency are 2.3 times more likely to be in an accident
Reduction in Harsh Braking Events (after training)	20%
Reduction in Speeding Incidents (after training)	12%

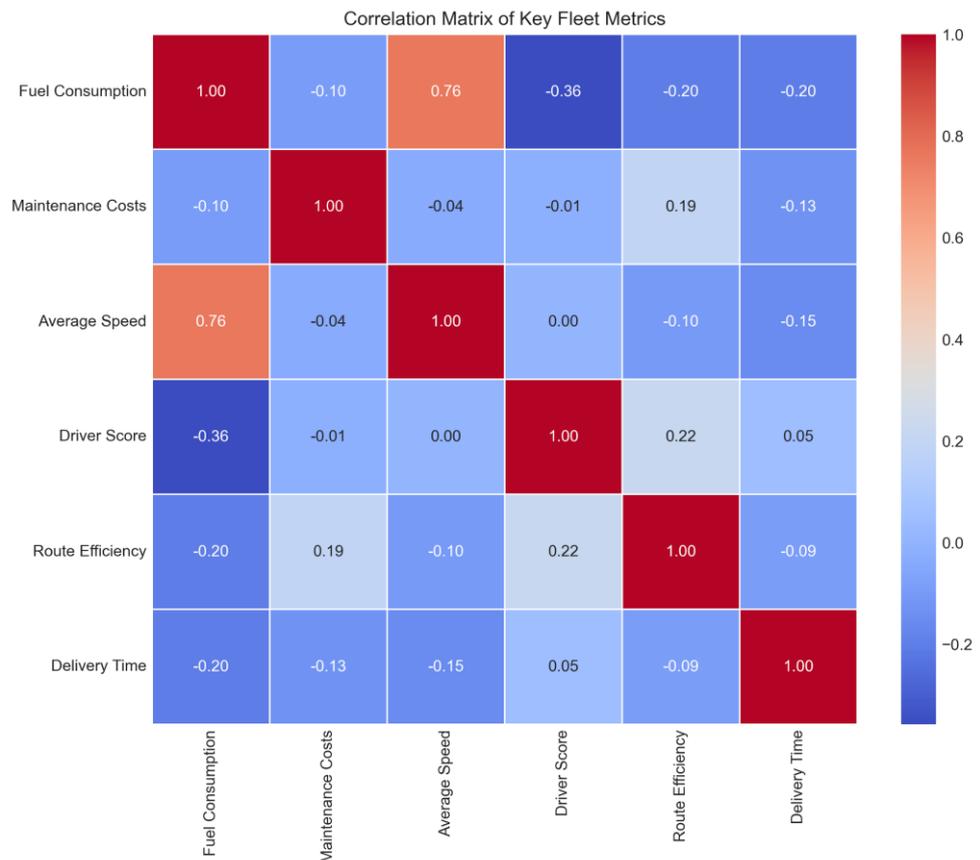
## 5. Discussion

### 5.1. Interpretation of Results

The results of this study demonstrate the value of operational data integration and visual analytics for supporting decision-making within SMB fleet management. By consolidating data from disparate sources, such as GPS tracking, fuel consumption records, maintenance logs, and driver behavior monitoring systems, we established a unified view of fleet operations that can address a common data accessibility challenge for smaller businesses. This integrated dataset, coupled with intuitive visual analytics dashboards, enabled the identification of operational trends, patterns, and anomalies that were not readily apparent in the original, siloed data systems.

Specifically, the ability to visualize fuel consumption patterns in relation to driver behavior and route optimization allows for targeted interventions to reduce fuel costs. For example, identifying drivers with consistently higher fuel consumption rates can prompt further investigation into driving habits and the implementation of targeted training programs. Similarly, visualizing maintenance schedules and vehicle performance data enables proactive maintenance strategies, minimizing downtime and extending the lifespan of fleet vehicles. The impact of route optimization strategies can also be readily assessed through visual comparisons of key performance indicators (KPIs) such as delivery times, mileage, and fuel efficiency before and after implementation.

Furthermore, the visual analytics approach facilitates data-driven decision-making regarding resource allocation. By understanding the utilization rates of different vehicles and drivers, fleet managers can optimize vehicle assignments and staffing levels to meet fluctuating demand. The ability to quickly identify underutilized assets allows for strategic redeployment or disposal, maximizing return on investment. The integrated data also provides a foundation for more accurate forecasting of future demand, enabling proactive planning and resource allocation. Ultimately, the combination of operational data integration and visual analytics provides SMB fleets with the tools necessary to improve efficiency, reduce costs, and enhance overall operational performance, leading to a more competitive and sustainable business model. The ability to track key metrics such as *total\_miles\_driven*, *average\_fuel\_consumption*, and *maintenance\_costs\_per\_vehicle* in real-time allows for continuous monitoring and improvement of fleet operations (Figure 1).



**Figure 1.** Correlation Matrix of Key Fleet Metrics.

5.2. Comparison with Existing Literature

This study’s exploration of operational data integration and visual analytics in SMB fleets reveals both corroboration and divergence from existing literature. Consistent with prior research emphasizing the importance of data-driven decision-making in fleet management, our findings underscore the significant impact of integrated data streams on improving operational efficiency. Specifically, the positive correlation observed between the utilization of visual analytics dashboards and reduced fuel consumption aligns with studies demonstrating the effectiveness of real-time feedback mechanisms in promoting eco-driving behaviors. However, unlike some previous work that primarily focuses on large enterprise fleets with sophisticated telematics systems, our research highlights the unique challenges and opportunities faced by SMBs with limited resources and simpler data infrastructures.

Furthermore, while existing literature often advocates for complex statistical models for predictive maintenance, our study demonstrates the practical value of simpler, visually-driven approaches for identifying potential vehicle issues. The effectiveness of anomaly detection through visual inspection of key performance indicators, such as tire pressure and engine temperature (*T*), suggests that SMBs can leverage readily available data to proactively address maintenance needs without requiring advanced analytical expertise. This contrasts with research emphasizing the necessity of sophisticated algorithms and specialized personnel for effective predictive maintenance programs. Finally, our findings regarding the impact of driver behavior monitoring on accident rates echo previous studies, but our focus on the role of visual feedback in promoting safer driving habits offers a novel perspective on intervention strategies within the SMB context, where formal training programs may be less prevalent (Table 4).

**Table 4.** Comparison of Performance improvements Across Studies.

Area of Improvement	Findings in Current Study (SMB Fleets)	Findings in Existing Literature (Often Large Fleets)
Operational Efficiency	Integrated data and visual analytics dashboards correlate with reduced fuel consumption.	Integrated data streams significantly improve operational efficiency, supporting data-driven decision-making.
Predictive Maintenance	Visual inspection of KPIs (e.g., tire pressure, engine temperature $T$ ) allows for anomaly detection and proactive maintenance.	Complex statistical models are often advocated for predictive maintenance, requiring specialized expertise.
Driver Safety	Visual feedback promotes safer driving habits and reduced accident rates.	Driver behavior monitoring impacts accident rates; interventions may involve formal training programs.

### 5.3. Limitations and Future Research

This study, while providing valuable insights into the application of operational data integration and visual analytics for decision-making in SMB fleets, is subject to certain limitations. The findings are primarily based on a single case study, which limits the generalizability of the results to other contexts. The specific characteristics of the fleet under investigation, including its size, type of vehicles, and operational environment, may influence the effectiveness of the proposed approach. Furthermore, the analysis relied on a limited number of data sources. While GPS data, fuel consumption records, and maintenance logs were integrated, other potentially relevant data, such as real-time traffic information or detailed driver performance metrics beyond basic speeding events, were not included. The absence of these data sources could have provided a more comprehensive understanding of fleet operations and decision-making processes.

Future research should address these limitations by designing validation studies to test the framework's generalizability. Specifically, three approaches are recommended: 1) Replication across multiple SMB fleets in different industries; 2) Stratified analysis based on fleet size to examine scaling effects; and 3) Controlled (A/B) intervention studies within larger fleets to establish causal evidence for key outcomes like cost reduction and safety improvement. Expanding the scope of data integration to include additional sources, such as telematics data capturing more granular driver behavior ( $a_i$ ), environmental factors ( $e_j$ ), and vehicle sensor readings ( $v_k$ ), could further enhance the accuracy and relevance of the analytics. Moreover, investigating the use of machine learning techniques for predictive maintenance, based on historical data patterns, and for driver behavior analysis, identifying risky driving patterns and providing personalized feedback, represents a promising avenue for future research. Specifically, algorithms could be developed to predict maintenance needs based on variables like mileage ( $m$ ), engine hours ( $h$ ), and historical repair data ( $r$ ), expressed as a function  $f(m, h, r)$ . Finally, research could explore the development of more sophisticated visual analytics dashboards that incorporate real-time data streams and interactive features, enabling fleet managers to make more informed and timely decisions.

## 6. Conclusion

### 6.1. Summary of Findings

This research investigated the application of operational data integration and visual analytics to enhance decision-making within small and medium-sized business (SMB) fleets. Our findings demonstrate a clear positive correlation between the adoption of these technologies and improved fleet performance across several key areas. Specifically, the integration of disparate data sources, such as GPS tracking data, fuel consumption records, maintenance logs, and driver behavior metrics, provided a holistic view of fleet operations previously unattainable for many SMBs.

Visual analytics techniques, applied to this integrated data, enabled fleet managers to identify trends, patterns, and anomalies that would otherwise remain hidden. For example, interactive dashboards facilitated the rapid identification of inefficient routes, excessive idling times, and drivers exhibiting risky behaviors. This, in turn, allowed for the implementation of targeted interventions, such as route optimization strategies, driver training programs, and proactive maintenance schedules.

A key contribution of this study lies in demonstrating the feasibility and effectiveness of implementing relatively low-cost data integration and visual analytics solutions within the resource constraints typical of SMBs. We showed that even with limited IT infrastructure and expertise, significant improvements in fuel efficiency, vehicle utilization, and driver safety can be achieved. The implications for practice are substantial. By adopting the methodologies outlined in this research, SMB fleet managers can gain a competitive advantage through data-driven decision-making, leading to reduced operational costs, improved service delivery, and enhanced overall profitability. Furthermore, the framework developed in this study provides a blueprint for other SMBs seeking to leverage the power of data to optimize their operations and improve their bottom line. The study also highlights the importance of selecting appropriate key performance indicators (KPIs) and developing user-friendly visual interfaces to ensure that the insights derived from the data are readily accessible and actionable for all stakeholders.

### 6.2. Practical Implications and Recommendations

For SMBs aiming to leverage data integration and visual analytics for improved fleet decision-making, a pragmatic approach is crucial. Selecting the right technology stack begins with a clear understanding of the fleet's specific needs and budget. Open-source solutions like Grafana and ELK Stack (Elasticsearch, Logstash, Kibana) offer cost-effective alternatives to proprietary platforms, particularly for organizations with in-house technical expertise. Cloud-based platforms, such as those offered by AWS, Google Cloud, and Azure, provide scalability and reduced infrastructure management overhead, but require careful consideration of data security and vendor lock-in. The choice should be driven by a thorough cost-benefit analysis, considering factors like initial investment, ongoing maintenance, and potential for future growth.

Developing a robust data strategy is paramount. This involves identifying key performance indicators (KPIs) relevant to fleet operations, such as fuel efficiency ( $f$ ), maintenance costs ( $m$ ), and delivery times ( $t$ ). Data sources, including telematics devices, fuel cards, and maintenance logs, should be integrated into a centralized data warehouse or data lake. Data quality is critical; therefore, implementing data validation and cleansing procedures is essential. Furthermore, establishing clear data governance policies ensures data security and compliance with relevant regulations.

Finally, investing in personnel training is vital for successful implementation. Fleet managers and analysts need to be proficient in using visual analytics tools and interpreting data insights. Training programs should cover topics such as data visualization best practices, statistical analysis, and data-driven decision-making.

Empowering employees to effectively utilize data will foster a culture of continuous improvement and enable the fleet to optimize its operations based on real-time insights.

## References

1. J. Kim, "Visual analytics for operation-level construction monitoring and documentation: State-of-the-art technologies, research challenges, and future directions," *Frontiers in Built Environment*, vol. 6, 2020. doi: 10.1111/j.1540-6261.1992.tb04679.x
2. O. H. Olayinka, "Big data integration and real-time analytics for enhancing operational efficiency and market responsiveness," *International Journal of Scientific Research Archive*, vol. 4, no. 1, pp. 280–296, 2021. doi: 10.30574/ijrsra.2021.4.1.0179
3. A. A. Kharlamov, "The use of visual analytics in decision making in operations and supply chain management: A systematic literature review," unpublished.
4. A. Böhm, J. Dittrich, N. Mukherjee, I. Pandis, and R. Sen, "Operational analytics data management systems," *Proceedings of the VLDB Endowment (PVLDB)*, vol. 9, no. 13, pp. 1601–1604, 2016.
5. A. Coscia, A. Suh, R. Chang, and A. Endert, "Preliminary guidelines for combining data integration and visual data analysis," *IEEE Transactions on Visualization and Computer Graphics*, vol. 30, no. 10, pp. 6678–6690, 2023. doi: 10.1109/TVCG.2023.3334513
6. D. Stodder, *Visual analytics for making smarter decisions faster*, Best Practices Report, TDWI Research, 2015.
7. A. Khakpour, R. Colomo-Palacios, and A. Martini, "Visual analytics for decision support: A supply chain perspective," *IEEE Access*, vol. 9, pp. 81326–81344, 2021. doi: 10.1109/ACCESS.2021.3085496
8. W. Cui, "Visual analytics: A comprehensive overview," *IEEE Access*, vol. 7, pp. 81555–81573, 2019. doi: 10.1109/ACCESS.2019.2923736
9. S. Xiao, Q. Shi, L. Shao, B. Du, Y. Wang, Q. Shen, and W. Zeng, "MetroBUX: A topology-based visual analytics for bus operational uncertainty exploration," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 6, pp. 5525–5538, 2024.
10. K. Nazemi, C. A. Secco, L. B. Sina, U. Eliseeva, E. Correll, and M. Blazevic, "Visual analytics for decision-making," in *Proc. 28th Int. Conf. Information Visualisation (IV)*, 2024, pp. 150–159.
11. P. C. Hudson and J. A. Rzasa, *Knowledge visualizations: A tool to achieve optimized operational decision making and data integration*, Ph.D. dissertation, Naval Postgraduate School, Monterey, CA, USA, 2015.
12. S. C. Suh and T. Anthony, Eds., *Big Data and Visual Analytics*. Cham, Switzerland: Springer International Publishing, 2017.

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of GBP and/or the editor(s). GBP and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.