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EFFECTIVENESS OF BIG DATA ANALYTICS IN FLEET OPTIMIZATION BY TRANSPORT COMPANIES IN MUTARE, ZIMBABWE

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ABSTRACT

Global trends in transport and logistics management show increase in the use of big data analytics (Moradi and Moradi, 2023). While data-driven fleet management brings improvements in fleet optimization, there are technological and organizational pitfalls related to these developments (Kumar and Singh 2020; Moradi and Moradi, 2023). This study therefore explored effectiveness of big data analytics in fleet optimization by transport companies in Mutare, Zimbabwe. The study applied a conceptual model that analysed the relationship between big data variables and fleet optimisation benefits in a multiple case study that generated data from staff in five purposively selected haulage transport companies that had sites in Mutare. The study established that diverse and inconsistent data sources negatively affected fleet optimisation and recommended that transport companies adopt data management statrgeties that use uniform formats that are internationally benchmarked.

Keywords: Big Data Analytics; Fleet Optimization.

BACKGROUND OF STUDY

The adoption of big data analytics in transport management has contributed to fleet optimization in transport industry (Kumar and Singh 2020). Global trends in transport and logistics show increase in the use of big data analytics collected from sources such as vehicle drivers, vehicle infrastructure, and external sources with the aim of improving efficiency, reducing operational costs, and improving customer satisfaction (Moradi and Moradi 2023). While there are notable improvements in data-driven fleet management in areas such as vehicle routing, scheduling, fuel consumption, maintenance, and driver performance (Kumar and Singh 2020), there are technological and organizational gaps and pitfalls associated with these developments (Moradi and Moradi, 2023).

One of the major pitfalls is that while big data analytics facilitate fleet management by analyzing huge amounts of data from GPS tracking systems, telematics, sensors, and mobile applications there are concerns that this goes with high operational costs and data quality challenges (Moradi, and Moradi, 2023). Companies in the United States and Canada are front runners in utilizing Big Data Analytics for fleet optimization (Zhang, Wang and Chen, 2024). For example, one company employs an application called On-Road Integrated Optimization and Navigation (ORION) that takes into consideration road, weather, and time windows for deliveries to devise the most economical paths. (Zhang *et al.,* 2021). While this application saves the company approximately ten million liters of fuel every year it has high operation and maintenance costs (Jones and Taylor 2020).

In the same vein, a survey by Kariuki (2020) established that data driven systems are plagued by challenges of data incompleteness and quality emanating from diverse sources such as GPS, sensors, telematics, and customers' locations. These challenges lead to erroneous predictions and non-optimal decision making. Similarly in Mexico, small and medium-sized transportation companies competing for routes fail to sustain high-cost big data analytics investments, hindering further growth and capacity to compete with big companies that continue to invest in sophisticated infrastructure, software and human capital (Gupta, 2023).

Majority of transport companies in Europe overcome inconsistent data challenges by implementing Internet of Things (IoT) devices along with telematics systems to collect, standardize, and transmit real-time quantitative vehicle data (Xie, Zhang and Liang 2020). However, inconsistent data formats hinder integration of datasets, leading to inefficiencies (Johnson 2020). Furthermore, differences in data collection frequencies across various sources result in temporal misalignments, reducing real-time decision-making capabilities (Kamble 2022). Some fleet operators in European countries have adopted Artificial Intelligence (AI) and Machine Learning (ML) to improve their big data analytics. Through AI tools, they predict maintenance needs, fuel-efficient routes and assess driver performance, all of which contribute to greater efficiency and lower operational expenses (Kamble, 2022). However, diverse and inconsistent data sources vary in format, structure, and granularity, making integration complex (Gupta, 2019). Challenges of inconsistencies emanate from missing values, duplicate records, and real-time data fluctuations (Gupta, 2023). According to Kamble (2022) poor data quality emanating from challenges such as sensor malfunctions, errors in manual data entry add a cumbersome prerequisite to data cleaning before useful analysis can be carried out. In Germany majority of companies face challenges of data quality. Data collection is neither consistent nor uniform because each manufacturer, logistics service provider, or software vendor has their own format and platform (Kamble 2022). This fragmentation hinders precision of maintenance models, dynamic routing algorithms, and analyses of fuel efficiency.

While huge transport cooperation's in Asian countries have made great strides in the use of AI, inconsistent data formats make it difficult to integrate datasets seamlessly resulting in inefficiencies in analytics (Fan, Han and Liu, 2024). The large volume of fleet data

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requires advanced storage and processing solutions, such as cloud computing and distributed databases. Without effective data integration, these analytics struggle to provide real-time insights (Brown and Wilson 2021). Lack of interoperability between these systems hinders seamless data sharing and limit effectiveness of big data analytics (Kumar and Singh, 2021). Inconsistent data leads to challenges of unreliable predictive maintenance, inaccurate fuel efficiency, and route optimization (Brown and Wilson, 2021).

Big data applications in fleet optimization are gaining popularity across African countries such as South Africa, Kenya and Nigeria, where the transport industry is growing because of increasing data quality and logistics efficiency. (Blaschke, Schoenher and Schroder 2020). In addition, African companies in Kenya, Uganda and Rwanda have integrated telematics that tracks location of vehicles, fuel usage, and driver performance as part of their centralized systems (Kamble 2022). This system significantly reduces the fragmentation of data and improves data consistency. These systems led to reduction in fleet operating costs. However, majority of transport companies do not have integrated systems due to fragmented and incomplete data that comes from several uncoordinated sources (Kariuki, 2020). According to Kariuki (2020) about 80% of African transport companies face problems with data quality negatively impacting on decision-making.

Big Data and Analytics are rapidly being adopted in fleet optimization in the Zimbabwean transport sector. However, fragmentation of data sources is a challenge as data is often stored in isolated systems making it difficult to collectively utilize data for comprehensive analysis Chikozho, and Mhlanga (2021). According to Mugari and Chikozho (2021), low integration of big data has shortfalls in analyzing traffic patterns and optimizing routes which results in increased fuel consumption and delays. While some companies in Zimbabwe have introduced systems that automate data mapping, cleansing, and transformation process to improve data consistency and integration coupled by quality audits (Kumar *et al.,* 2018), fleet data is usually aggregated from numerous sources that utilize various formats and standards. This variety makes data integration more complicated (Kumar, Singh and Gupta 2028).

Some cross-border transport and logistics companies based in Zimbabwe, specializing in transporting bulk fuel, LPG, and general cargo across Southern Africa have made strategic investments in Big Data Analytics to enhance fleet optimization and overall operational efficiency (Mugari and Chikozho, 2021). Despite the benefits that have accrued, challenges of unreliable real-time data transmission from vehicles to control centers persist. This has led to challenges such as data loss or incomplete data logs hindering route optimization, fuel management, and predictive maintenance. (Mugari, and Chikozho, 2021). The forgoing challenges prompted this paper to investigate the effectiveness of big data analytics in fleet optimization by transport companies in Mutare, Zimbabwe.

Statement of the problem

The adoption of big data analytics in transport management has contributed to fleet optimization in transport industry. While global trends in transport and logistics show increase in the adoption of data driven fleet management with benefits that accrue, there are technological and organizational challenges such as high operational costs, diverse and inconsistent data sources and data quality. This paradox has prompted this paper to investigate effectiveness of big data analytics in fleet optimization by transport companies in Mutare, Zimbabwe.

Research objectives

1. To analyze the distribution of data sources in fleet management by transport companies in Mutare.
2. To explore how diverse and inconsistent data sources affect big data analytics in fleet optimization in transport companies in Mutare
3. To examine organizational issues affecting big data analytics in fleet optimization by transport companies in Mutare
4. To examine technological barriers in big data analytics for fleet optimization by transport companies in Mutare
5. To identify strategies for improving data inconsistency in fleet analytics by transport companies in Mutare.

Research questions

1. What is the distribution of data sources in fleet management by transport companies in Mutare?
2. How does diverse and inconsistent data sources affect big data analytics in fleet optimization in transport companies in Mutare?
3. What organizational issues affect big data analytics in fleet optimization by transport companies in Mutare?
4. How do technological barriers in big data analytics affect fleet optimization by transport companies in Mutare?
5. What strategies can improve data inconsistency in fleet analytics by transport companies in Mutare?

REVIEW OF RELATED LITERATURE

Conceptual framework

Big data variables **Fleet optimization variables**

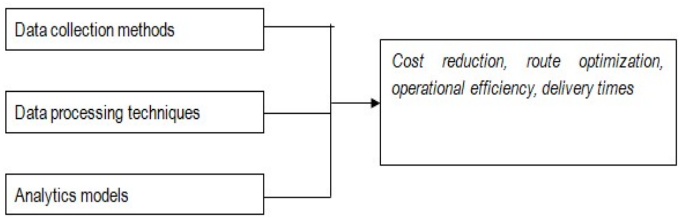

Figure 1: Model of fleet optimization using big data

The conceptual framework informs on the relationship between big data analytics and fleet optimization. The model seeks to solve fleet management problems by focusing on how big data variables of data collection, processing and analysis influence issues of cost reduction, route optimization, and operational efficiency

Theoretical Framework

Resource Based View (RBV) (Wang and Zhang 2023).

This is a theoretical approach that informs on how transport companies attain competitive edge through the utilization of technological resources and organizational abilities (Wang and Zhang 2023). Leveraging on technological and organizational efficiencies, a company can create data driven synergies that improve fleet optimization. Big data analytics is a significant resource in fleet optimization that can add competitive advantage by analyzing vast amounts of data on vehicle performance, driver actions, and customer preferences can unlock competitive advantages.

Dynamic Capabilities Theory (Kamble, 2022)

Formulated by Teece and Shuen (1990), the theory was developed by Kamble (2022) to focus on adaptability and innovation in sustaining competitive advantage. It focuses on the company's capacity to assimilate, develop, and organize internal and external capabilities to respond to demands from the dynamic environments. Adoption of Big data is a form of dynamic capabilities that enables the transport company to respond to changing markets, improve fleet performance, and react to customer requirements instantly. Built upon threats and opportunities, big data leads to organizations collecting large amounts of data and analyzing it to make rational resource allocation decisions.

Review of empirical studies

The effect of data sources on fleet management by transport companies

A study by Baker (2022) analyzed a data source called ORION used by Parcel Service Company in Canada to optimize routes. The study generated data from drivers, logisticians, managers and IT technicians who reported that the data source used advanced algorithms and big data analytics to examine millions of routes and determined the best routes drivers should use in order to achieve maximum efficiency. The participants expressed that ORION saved the company fuel, lowered carbon dioxide emissions and improved efficiency of deliveries by enabling drivers to deliver more goods in a shorter period. The study concluded that while ORION integrated data across multiple systems, including package tracking, delivery confirmation, and current traffic, inconsistency in the quality of data across different systems present challenges in optimizing routes.

The effect of diverse and inconsistent data sources on big data analytics in fleet optimization

A study by Lakens and Caldwell (2022) explored data inconsistent challenges that faced a parcel delivery company in the city of Houston in USA. The study was interpretivist generating data from company staff. Results show that while the company attempted to integrate data from multiple systems of package tracking and delivery confirmation, inconsistency in the quality of data presented challenges. The study recommended deployment of more effective data management systems that standardize data in a common format.

Organizational issues affecting big data analytics in fleet optimization

A study by Smith and Jones (2021) investigated organizational issues affecting operational efficiency at an international delivery company in the UK. Generating data from staff surveys, the study established issues of data inconsistency from various sources such as third-party providers in some receiving countries internal systems, and some customers in less developed countries. The inconsistency in the data created challenges in developing a single view of fleet performance. Inconsistency in data quality coming from diverse sources created unreliable analysis, which affected decision-making. The study recommended use of Internet of Things devices to increase data security

Technological barriers in big data analytics for fleet optimization

A multiple case study by Sun, Wang and Luo (2022) Generated data from transport companies in Mexico City. Through interpreting data from company staff the study established that the companies adopted Internet of Things technology to boost fleet management capabilities. For instance, vehicle sensors gave real-time insights on vehicle's performance, the drivers' behavior, and environmental issues. By using data integration strategies, data quality and predictive analytics, companies improved their operational efficiency and sustained competitiveness. However, integrating Internet of Things data with local systems was a challenge due to the diversity of the data. Various sensors gave different data in different data types, and this made it difficult to analyze the data.

RESEARCH PARADIGM

The study was grounded in interpretivisim where reality was socially constructed from the context perspective (Patton 2015). The staff in the logistics companies created meaning from their experiences within their specific institutional contexts. The study constructed knowledge qualitatively from beliefs, values and perceptions of company staff. Their motivations and expectations formed the basis of knowledge generated from their interpretation of reality of big data and fleet optimization.

Research approach

The study adopted qualitative approach which enabled generation of in-depth data from exploration of company staff's views and experiences (Patton 2015). Qualitative methodology allowed flexibility and depth in examining complex connection between big data analytics and fleet optimization as socially constructed evolving innovation.

Research design

The study adopted a multiple case study design. The cases were the companies that were purposively sampled for the study, and each case was further broken down into cases of staff whose jobs were similar across the companies (Saunders, Lewis and Thornhill 2019. The case study method was selected because it enabled in-depth, holistic and contextually grounded examination of big data analytics and fleet management variables as closely intertwined variables in their contexts

Population

The city of Mutare is the third largest town in Zimbabwe located along the Forbs border post that service as the Beira route gateway to the sea through Mozambique. This route connects to countries to the north of Zimbabwe namely, Zambia, Tanzania and Malawi. While hundreds of haulage trucks pass through Mutare every day, the study focused on 13 haulage transport companies that had bases in the city of Mutare with trucks that operated in the Beira route. Data was generated as views from managers, truck drivers, maintenance staff, IT staff and logistics officers who worked at these 13 sites.

Sample

From the 13 transport companies, 5 largest companies were purposively sampled. From each company one managerial staff, three drivers, one maintenance staff, one IT staff and one logistics staff were purposively sampled to create a multiple case sample of 5 managers, 15 truck drivers,5 maintenance workers, 5 Information Technology (IT) staff and 5 logisticians, making a total of 35 participants.

Sapling techniques

Purposive sampling

Purposive sampling was used to select the five companies from the 13. Purposive sampling selected participants from each company (Sekaran and Bougie, 2018). This was a deliberate selection of companies and participants based on relevance of the data to be generated. The sampling technique enabled the researcher to select sources of data directly capable of providing primary data from real life experiences.

Convenient sampling

Convenience sampling was used to select truck drivers. This was a none-probability sampling technique that was based on convenience and accessibility of the drivers (Sekaran and Bougie, 2018). In all cases the drivers were accessed when they passed through the company site for refueling and servicing. They voluntarily completed the questionnaire during their resting times.

Instruments

Semi-structured interviews

Semi-structured interviews were used to generate data from managers, maintenance, IT and logistics staff. The interviews had features of both open and closed questions (Saunders, Lewis and Thornhill 2019). Open ended questions enabled the participants to express their own opinions while closed questions collected bio-data. The questions were constant with all participants enabling coverage of all areas. At the end of the interview the participants were asked to give open views.

Questionnaires

A total of 15 questionnaires were given to truck drivers. The questionnaire was structured in such a way that it contained both open and closed-end questions. The use of structured questions enabled the drivers to respond to the questions quickly. (Saunders, Lewis and Thornhill 2019). While open ended questions were few, enabling the drivers to elaborate on issues freely.

Data generation techniques

The researcher made appointments through company management who facilitated arrangements for interviews with junior staff. After the interviews, the research administered questionnaires to available drivers.

Data analysis techniques

Data analysis was mainly qualitative and involved breaking down data into manageable units, coding, and synthesizing to produce emerging themes from cases.

Ethical considerations

The researcher informed all the participants about the purpose of the study, its scope and intended methods of data generation (Ngozwana, 2018). The researcher guaranteed participants that their professions could not be harmed because of participating in the research. Confidentiality and anonymity were assured by through removing elements of identity at data generation in the study. Participation was voluntary with no cohesion of participants.

Demographic characteristics of respondents

Distribution of respondents by gender

Data on distribution of respondents by gender show that 24(69%) were males and 11(31%) were females. This shows that majority of the staff in transport companies were male. While the results cannot be generalized, they depict a male dominated workplace where the research took place.

Distribution of workforce by level of education

Data on the distribution of workforce by level of education show that all five managers had master's degrees in supply chain and logistics. All five logisticians had bachelor's degrees in supply chain and logistics. All IT staff had higher national diplomas in IT. All drivers had class 2 licenses. These findings reflect a high level of staff expertise in respective trades in the companies.

Distribution of workforce by work experience

Data on distribution of workforce by work experience show that 30(85%) of the respondents had more than 8 years' work experience in their respective companies. This shows low rates of staff turnover and substantial work experience to enable provision of insightful data on company operations.

Distribution of data sources in fleet optimization

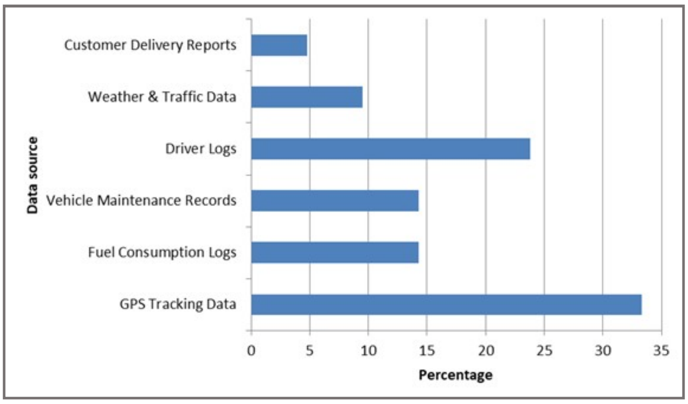

Figure 4.5 Data source in fleet optimization

Source: Primary data

Data from drivers show that Driver Logs and GPS Tracking Data were the most popular sources in fleet optimization. This indicates a heavy emphasis on tracking driver behavior. On the other hand, data from vehicle maintenance staff show that vehicle maintenance records were frequently used more than weather and traffic data. These findings are in line with Lakens and Caldwell (2022) who recommended deployment of more effective data management systems that standardize data in a common format.

How diverse and inconsistent data sources affect big data analytics in fleet optimization

Data from managers show that the major challenge emanating from data inconsistencies was that of missing data. For instances the managers said missing data affected decision making in fleet management. Data from IT technicians show that the major challenge was duplicate entries and contradictory data formatting issues. For instance, one of the technicians said that formatting prevented real time data analysis. Data from logisticians show that the major problem of data inconsistencies was that of duplicate entries that led to inconsistencies. This shows that data redundancy was a prevalent obstacle in fleet data systems. These findings confirm to Baker (2022), who concluded that inconsistency in the quality of data across different systems present challenges in optimizing routes.

Effects of inconsistent data on fleet management

Table 1: Distribution participants' views on effects of inconsistent data on fleet optimization

Case	Effect on fleet optimization
Manager A	Data inconsistence's led to operational delays
Manager B	Inconsistent data led to unnecessary cost
Manager C	Decisions are often postponed due to data reliability concerns
Manager D	Customer satisfaction is negatively affected by data inconsistence's
Manager E	Staff productivity is reduced by time spent on resolving data issues

Data on table 1 shows that managers have had varied effects within their respective companies. However, data emerging from IT staff, logistics officers and drivers pointed out the effects on working environment and customers. One driver said, "Customer satisfaction has been negatively affected by data inconsistencies as the inconsistencies lead to operational delays and reputation." While all participants agreed that inconsistent data led to unnecessary costs, one driver said driver "productivity was significantly reduced by time spent resolving data issues." Sun, Wang and Luo (2022) strongly support that data inconsistencies is a challenging to operational efficiently as decisions are made basing on inconsistent data that would have been collected.

Organizational challenges emanating from data inconsistencies in fleet optimization

The following emerging themes merged with participants as challenges emanating from data inconsistency

Poor Decision-Making

Manager A was of the view that data inconsistencies affected decision making since fleet managers depend on data analytics to make decisions such as route optimization, fuel efficiency, and cost control. Manager B said inconsistency in data produced erroneous analyses lead to poor strategic management. Manager C said that inaccurate data caused misallocation of assets such as mismatching wrong trucks to routes. Manager D cited unrecognition of underutilized assets that caused inefficiencies and increased costs of operations. These findings confirm that decision making inefficiencies caused by inconsistencies in data lead to inefficiencies that led to increased costs on fuel maintenance and labor invested (Baker 2022). Wang and Zhang (2023) adds that firms that are unable to effectively make decisions in managing their fleet because of inconsistencies in data put themselves in a competitive disadvantage.

Operational Inefficiency

Emerging themes from logisticians were of operational inefficiencies. For instance, Logistician A, said that discrepancies in data were the earliest effects of data inconsistencies. Differences in data from GPS monitoring benchmarking and fuel consumption records produced incorrect performance reporting that impacted on budgeting, forecasting, and performance appraisal. Logistcian B said that inconsistent maintenance activity records caused unexpected breaks that affected vehicle service schedules. This result in unnecessary downtime and more expensive repair costs. Logistician C said that inefficiency not only increased the burden on the operation capacity of the fleet but on the cost of other subsidiary fleet costs. Logistician D expressed those discrepancies among vehicle records led to reactive and unplanned servicing. Logistician E articulated that unplanned data breakdowns caused service interruptions and added costs on repairs and lost productivity. These findings are in line with Wang and Zhang (2023) who concluded that inconsistencies in vehicle maintenance records cause unexpected downtime when serviceable vehicles are not serviced immediately, leading to unexpected disrupting service delivery.

Compliances and Regulation Risks

Emerging themes from drivers show that incomplete and inconsistent data had adverse consequences for compliance. For instance, driver A said that inconsistency in data caused regulatory and no compliances on emissions testing and on safety standards inspections. These violations attracted penalties and delivery schedule disruptions. Driver B said that inconsistencies in data adversely impacted on the reputation of the company. Driver C observed; "discrepancies in vehicle maintenance records make it difficult for the data presented to the regulators to be accurate." While driver D said that lack of transparency on records increased the administrative period of examination of administration's requirements and increased chances of penalties. These findings conform to Smith and Jones (2021), who established that inconsistency increased the risks on fleet operation effectiveness.

Technological barriers in big data analytics for fleet optimization by transport companies in Mutare

The following emerging themes emerged from data generated from IT technicians

Data Quality Problems

IT technician (A) said that incorrect readings by sensors, human error in inputs, and stale data caused inaccuracy in the datasets and impacted the validity of analytics. IT Technician (B) said that incomplete data distorted the analysis and provided wrong insights regarding fleet performance. IT technician (C) identified negative effects on validity of analytics such as fuel forecasting and route planning. IT technician D cited inadequate data quality of typing errors in data entry and use of outdated data. IT technician E expressed lack of analytical tools as a major technological barrier. He said that tools with poor analytics capabilities struggle with complex datasets leading to production of oversimplified and incorrect insights. This was in line with Zhang *et al.,* (2021) who said that incompatible tools are prone to creating data silos, making data consistency difficult. Kumar *et al.,* 2018) adds that inadequate processing capacity can delay real-time analytics leading to out-of-date insights and impact the efficiency of operations.

Strategies for improving data inconsistency in fleet analytics

Data from managers converged on integrating all systems to share data automatically. From IT technicians it emerged that establishing company-wide data entry and formatting standards was a main strategy. Transport logisticians agreed on employing cloud-based solutions for centralized data access. The logisticians suggested automating data validation with alerts for inconsistencies. Drivers suggested updating old systems and vehicle hardware and software.

All staff suggested training all employees in appropriate data treatment and tools handling. The findings are in line with Wang, Zhao and Chen (2023) who proposed a multi-dimensional framework which consists of technology-based solutions (cloud systems, automation) as well as traditional methods (like data standardization and employees' training).

CONCLUSIONS

In the light of the forgoing findings, the study made the following conclusions:

1. Inconsistent and diverse data sources create problems in the effectiveness of big data analytics in fleet optimization.
2. Platforms that provide data in different formats and levels of quality lead to data unreliability resulting in ineffective decision making.
3. Data inconsistencies affect the application of big data analysis in fleet management resulting in operational inefficiencies.
4. Companies face challenges in integrating, processing and analyzing data resulting in poor optimization.

Recommendations

In the light of the above conclusions, the study made the following recommendations:

1. Transport companies must define standard data protocols, deploy automated validation tools, and create strong governance over consistency, accuracy and the reliability of the different data sources.
2. Transport companies must adopt data management strategies that address data inconsistencies to maximize benefits generated by big data analytics in fleet optimization.
3. Transport companies must adopt common data formats and real-time data systems and automatic tools for data cleaning, organizations to improve data dependability and accuracy,
4. Transport companies must make decisions based on data that is responsive and optimized operations across the entire fleet.

FUTURE RESEARCH

This study was a multiple case study and therefore its results cannot be generalized. The study used interpretivist philosophy that generated data from what staff in the transport companies saw as reality and therefore was subjective. Future research must focus on quantitative methodologies that collect objective data that can be generalized.

REFERENCES

Lakens D & Caldwell. (2022). A Simulation-Based Power Analysis for Factorial Analysis of Variance Designs. Advances in Methods and Practices in Psychological Science, 5(1), 1-14.

Baker, J. &. (2022). Maintenance Management in Fleet Operations: A Data-Driven Approach. International Journal of Fleet Management, 12(1), 23-37.

Batini, S. &. (2009). Data Quality: Concepts, Methodologies and Techniques. Springer.

Blaschke, Schoenherr & Schröder. (2020). Big Data and Analytics in Supply Chain Management: A Literature Review. International Journal of Physical Distribution & Logistics Management,, 50(7/8), 635–666.

Bouncken, et al. (2021). Data Validity in Business Research Journal of Business Research.

Brock, D., & Khan, O. (2022). The state of big data analytics in North American logistics and transportation, Journal of Business Logistics, 43(1), 30-49.

Brown & Wilson. (2021)., Data-driven decision-making in transport logistics. Transport Analytics Journal, 15(3), 45-60.

Chikozho, C., & Mhlanga, D (2021). Big Data Analytics in the Zimbabwean Transport Sector: Opportunities and Challenges. African Journal of Science, Technology, Innovation and Development, 13(4), 1-12.

Christopher, M., (2021). Logistics & Supply Chain Management (5th ed.). Pearson Education.

Creswell, J. W. (2014). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (4th ed). Sage Publications.

Davenport, &. H. (2013). Competing on Analytics: The New Science of Winning.

Etikan I & Bala K. (2023). Sampling and Sampling Methods. International Journal of Statistics and Medical Informatics, 2(1), 1-10.

Fan J, Han F, & Liu H . (2024). Challenges of Big Data analysis. Natl Sci Rev 1:293–314.

Gupta, &. R. (2023). Heterogeneous data integration in smart transport systems. IEEE Transactions on Intelligent Transportation, 20(5), 112-130.

Johnson, R. (2020). Regulatory Compliance in Fleet Management: The Importance of Accurate Data. Compliance Journal, 8(2), 34-42.

Jones, & Taylor., (2020). Optimizing fleet performance through data analytics. Logistics Review, 10(1), 25-40.

Kamble, S. S. (2022). Big data-driven sustainable supply chain performance measurement: A review and framework for implementation. International Journal of Production Research, 57(18), 1-27.

Kariuki, O. &. (2020). The role of big data analytics in improving public transport safety in Kenya. Journal of Transport and Supply Chain Management, 14(1), 1-10.

Kumar & Singh. (2021). Interoperability challenges in fleet data integration. International Journal of Transport Systems, 9(3), 66-82.

Kumar, A & Singh, R. (2020). Big Data Analytics in Fleet Management: A Review Journal of Transportation Technologies, 10(3), 123-135.

Kumar, Singh & Gupta. (2024). Impact of Data Quality on Fleet Management Performance. Journal of Transportation Management, 29(2), 45-58.

Mishra, Patel & Sharma,. (2020). Data Analytics in Fleet Management: Challenges and Opportunities." Transportation Research Part E: Logistics and Transportation Review, 134, 101-115.

Moradi, F., & Moradi, F. (2023). Big Data Analytics in Transportation Systems: Applications, Challenges, and Future Trends. IEEE Access, 8, 116-130.

Mugari, T, & Chikozho, C. (2020). Challenges of Data Collection in the Transport Sector in Zimbabwe: A Case Study of Harare. Journal of Transport and Supply Chain Management, 14(1), 1-10.

Ngozwana, N. (2018). Ethical Dilemmas in Qualitative Research Methodology: Researcher's Reflrctions. International Journal of Educational Methodology, 4(1). 19-28.

Patton, M. Q. (2015). Qualitative Research & Evaluation Methods (4th ed.). Sage Publications.

Sánchez-Martínez GE, Munizaga M. (2016). Workshop 5 report: harnessing big data. Res Transp Econ 59:236–241.

Sarstedt, Bengart,Shaltoni, & Lehmann. (2018). The use of sampling methods in advertising research: A gap between theory and practice. International Journal of Advertising, 37(4), 650-663.

Saunders, Lewis, & Thornhill. (2019). Research Methods for Business Students (8th ed.). Pearson Education.

Sekaran, & Bougie. (2018). Research methods for business: A skill building approach.

Singh, & Masuku,. (2022). Sampling Techniques & Determination of Sample Size in Applied Statistics Research. International Journal of Economics, Commerce and Management, 10(4), 33-50.

Smith & Jones, (2021). Resource Allocation in Fleet Management: The Role of Data Consistency. Fleet Management Review, 15(3), 67-79.

Smith, J. &. (2019). Predictive maintenance using AI in fleet operations Artificial Intelligence in Transport, 11(4), 101-120.

Stirling, Nixon & Takarangi. (2021). No more than discomfort: the trauma film paradigm meets definitions of minimal-risk research. Ethics & Behavior, 1-17.

Sun, Wang,, & Luo. (2022). Ensuring data quality in transport analytics. Journal of Data Management, 13(2), 76-92.

Taherdoost, H. (2023). Validity and Reliability of the Research Instrument: How to Test the Validation of a Questionnaire/Survey in Research, International Journal of Academic Research in Management, 11(3), 99-116.

Wamba, Gunasekaran, Akter, Ren, Dubey, & Childe. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. , Journal of Business Research, 70, 356–365.

Operational Efficiency in Fleet Management: The Role of Data Consistency. Journal of Business Logistics, 42(3), 215-230.

Wang, X, & Zhou, J. (2015). The application of big data in transportation. Procardia Engineering, 137, 640-646.

Wang, Y, & Zhang, Y (2023). Data Quality in Big Data: A Review. Journal of Data and Information Quality, 11(2), 1-25.

Wang, Zhao & Chen, X. (2020). Big data processing in fleet management. Transportation Research Journal, 16(1), 40-55.

Xie K, Zhang, Z, & Liang, L. (2020). Big data analytics for transportation: Opportunities and challenges. Transport Reviews, 40(2), 190-213. Xie K, Zhang, Z, & Liang, L.

Zhang et al., 2. (2021). Big Data Analytics in Transportation Systems: Applications, Challenges, and Future Trends.

Zhang, Wang & Chen. (2024). The role of data quality in big data analytics for fleet management. Journal of Intelligent Transportation Systems, 23(4),

Zhou, C. &. (2020). Supply chain data analytics: A review and implications for the digital era. Decision Support Systems, 138, 113429.

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