TOWARDS SUSTAINABLE MOBILITY IN SOUTH AFRICA: THE ROLE OF LANE CHANGE STUDIES

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ABSTRACT

South Africa's highways face challenges related to road safety, congestion, and the integration of diverse transit modes. Unsafe and inefficient lane-changing manoeuvres (especially in high-traffic corridors and weaving sections) are major contributors to traffic crashes and reduced mobility. While lane changing has been extensively studied internationally, its research and application in South Africa is still limited. There is need for localized, high-quality data acquisition and analyses, and adaptation of global best practices to South Africa's traffic mix. Lane change observations inform design of safer road infrastructure, optimize traffic management strategies, and support evidence-based safety policy interventions. This essay briefly reviews lane change research and presents driver behaviour data sources and some of the effective solutions that could be derived from comprehensive empirical studies of driver lane-changing behaviour on South African roads.

Keywords: Lane changing, Safety, Traffic flow, Capacity, Models.

1. INTRODUCTION

Urban mobility in Southern Africa faces multifaceted challenges, including increasing vehicular congestion, high crash rates, and environmental concerns. The lack of accurate data sources also hinders the development and implementation of effective traffic management strategies on South African roads (Venter, 2010). Understanding driver behaviour, including lane-changing (LC) patterns, is pivotal to devising potent mobility solutions to these effects. Empirical LC studies, grounded in real-world observations and data analyses, provide a robust foundation for researching these behaviours and their implications on various aspects of traffic dynamics (Yuan et al., 2023b; Ali et al., 2025).

Car following and lane changing are two major driving tasks in traffic flow and form an important part of traffic flow theory. Lane change behaviour is more complex than the safety risk of following behaviour, because the completion of a lane change manoeuvre has a number of conditions, such as identifying the target lane and assessing the time and distance gaps (Ma and Li, 2023). Studies indicate that lane changing may cause a reduction in capacity and generate shockwaves in both lanes, create bottlenecks on the freeway, and reduce traffic safety (Ali et al., 2025). It is thus crucial to establish the influence of lane changes on the capacity, stability, and breakdown of traffic flows on roads in South Africa.

Current research lacks quantitative data on lane-changing behaviour in South African contexts which presents a significant knowledge gap in understanding its impact on local traffic flow and safety. Therefore, systematic, data-driven studies on lane-changing are required to establish the existing behaviour which is essential in developing realistic and accurate LC (Statistical and Machine Learning) models (Rahman et al., 2013; Guo et al., 2018). These models can be used to (derive and) test various interventions on highway performance, traffic safety, and management. This essay discusses lane changing, study data sources, and the solutions LC research offers to transport challenges in South Africa.

2. LANE CHANGE RESEARCH STUDIES – A BRIEF REVIEW

Lane changing (LC) is one of the most fundamental and indispensable driving manoeuvres for vehicles. A lane change involves the driver moving the (subject) vehicle laterally from one (current) lane to another (target) where both lanes have the same direction of travel (Fitch et al., 2009; Das et al., 2020). The process involves four steps: generating intent to change lanes, assessing conditions for doing so, selecting a lane to move into, and finally carrying out the lane change to the desired lane (Vechione et al., 2018; Ma and Li, 2023).

There are generally two types of lane changes, that is, Mandatory (MLC) and Discretionary (DLC) (Ben-Akiva et al., 2006; Bham, 2011). MLC occurs when drivers have to change lanes in order to connect to the next link on their path, bypass a lane blockage downstream or avoid entering a restricted use lane, and the main motivation is to reach the planned destination. DLC is performed when the driver is not satisfied with the driving condition(s) in the current lane and wishes to gain some speed advantage, safety improvements, or both. Lane change behaviour is affected by a variety of factors, such as individual driver socio-demographic characteristics (gender, age driving experience, education), geometry, traffic conditions, vehicle dynamic parameters, and the time of travel in the day (morning, afternoon, or evening times) (Kesting et al., 2007; Liu et al., 2023). Lane changing is a complex driving operation that has a significant impact on traffic flow dynamics (Yuan et al., 2023a). It can lead to shock waves and increase the probability of congestion (Gao and Levinson, 2023; Wang and Cheng, 2023), reduced traffic safety (crashes, side swipes or near misses) (Fitch et al., 2009; Shawky, 2020) and reduced capacity due to moving obstructions (Rahman et al., 2013; You et al., 2015; Liu et al., 2023).

Lane change studies require systematic data collation and analysis related to drivers' LC manoeuvre aspects which typically include traffic flow metrics (e.g., flow, density, or speed, headway), driver physiological parameters (e.g., eye movements and head rotation angle) and safety indicators (crashes, near-misses or other conflicts) (Yuan et al., 2023b). These use various methodologies including field observations, video capture and analysis, sensor data collection, and simulation modelling (Ali et al., 2025). Lane changing has been extensively studied right from traffic flow theory, vehicle simulation models and optimization, to the incorporation of behavioural factors and safety (Ma and Li, 2023). With the advent and rapid development of artificial intelligence (AI), research has gradually shifted to Connected and Autonomous Vehicles (CAVs), facilitating the development of various lane change prediction models and vehicle trajectory planning models. Lane Change models proposed over the past decades are divided into two categories, that is, analytical models (rule-based and discrete choice-based) and data-driven models (based on Neural Networks (NN), Support Vector Machine (SVM), Bayesian Filtering (BF), Fuzzy Logic, Reinforcement Learning, and Deep Learning) (Moridpour et al., 2010; Rahman et al., 2013; Zheng, 2014; Xie et al., 2019; Liu et al., 2023; Ma and Li, 2023). Moving forward, driverless intelligent vehicles are poised to be the future of automobiles and mobility, and this will be a key direction for future research.

3. ADDRESSING SOUTHERN AFRICAN MOBILITY CHALLENGES

The South African vehicle and driver population is heterogeneous with a traffic mix that includes modes like passenger cars and public transport (minibus taxis and buses) (Vanderschuren, 2006). In varied road conditions, in these impact high-order road performances, it is crucial to understand how driver behaviour (including lane changing) affects traffic flow dynamics on these roads. This effort needs reliable and accurate data which can be fused, mined and interpreted into meaningful strategies for addressing mobility challenges like safety. Establishing the factors affecting lane changing behaviour through empirical studies on the road network (as in high-traffic corridors and freeway weaving sections) allows authorities to craft appropriate mitigating measures in terms of road design processes and traffic management and control strategies (Chang and Kao, 1991).

LC studies, starting with empirical observations and analyses will identify aspects of this behaviour and derive impacts on traffic safety and overall road capacity. The data is a key input into LC models adapted for the South African driver, vehicle, and road environment.

3.1 Potential Resources for Driver Lane Change Behaviour Data

From Ali et al. (2025), lane change behaviour has been extensively studied internationally (particularly in the global North). However, LC research and application in Southern Africa (and Africa at large) is still very limited. Accessing comprehensive datasets on driver behaviour (including LC) would be a good starting point but this is a big challenge due to the few publicly available resources (Venter, 2010). Some of the avenues for valuable data and insights to support meaningful research in this area in South Africa are discussed below.

a. SANRAL's Freeway Management System (FMS)

This is a network of technologies and systems designed to enhance the efficiency and safety of South African national roads (Kriel, 2017; SANRAL, 2025). The FMS includes the collection, processing, and dissemination of real-time traffic data. It relies on Intelligent Transportation System (ITS) technologies to monitor and manage traffic flow, detect incidents, optimise response times, and improve overall road safety and efficiency. This is through data collection and analysis. The FMS data collection infrastructure includes CCTV Cameras which are strategically placed along major freeways to monitor traffic conditions and detect incidents in real time and Vehicle Detection Stations where sensors are mounted on camera poles, gantries and streetlights to collect data that can compute traffic volumes and speeds.

b. Driver Simulator Studies

Driving simulators have been used to study traffic-related issues and their validity has been generally accepted in the transport research community (mostly road safety and driver human factors). They allow for control of the variables and acquisition of data on driver lane-changing behaviour under different conditions (Hess et al., 2020; Wang and Cheng, 2023). In South Africa, the Council for Scientific and Industrial Research’s (CSIR’s) AV Simulation SIMFLEX driving simulator, housed on their Scientia campus (CSIR, 2025) and the University of Cape Town’s (UCT’s) research-grade vehicle driving simulator (the vSIM) (UCT, 2015) may be used to obtain complete and accurate microscopic experimental driving data on LC behaviour to aid research on the subject.

c. Naturalistic Driving Studies (NDS)

The Naturalistic Driving Studies (NDS) methodology refers to an unobtrusive approach to studying driver behaviour in which an instrumented vehicle is equipped with eye-tracking and video technology allowing researchers to detect and analyse how the vehicle driver, the vehicle itself, the road and other traffic activities relate to each other in normal circumstances (Venter and Muronga, 2016). It is more controlled than field research, and its data is more representative of real traffic conditions in relation to simulator data (Yang et al., 2019). The CSIR Transport Safety Laboratory (TSL) features an instrumented vehicle (known as the Drive Lab) equipped with sensors to collect data on driver behaviour and the environment on the road (CSIR, 2025). This may be used to obtain information about LC types and their relative frequencies as they occur in a naturalistic environment (real-world roads), as opposed to being performed as instructed by an experimenter.

d. High-Frequency GPS Big Data From Probe Vehicles

Floating car data (FCD) are a source of traffic information passively reported from within the traffic stream by GPS-enabled probe devices commonly carried in vehicles, including smartphones, on-board navigation devices, and vehicle tracking systems. FCD are available over road networks without roadside sensors and communications infrastructure. Commercial FCD are provided by various third-party traffic data concerns such as TomTom, INRIX, and HERE who collect, process, store, and sell FCD in highly accessible and usable formats (Bruwer et al., 2023). In South Africa, FCD is commercially available from TomTom and Tracker, which partners with companies like Innovative Transport Solutions (ITS). Li et al. (2020) caution that the intermittent trajectory data obtained from FCD are conventionally inadequate to reconstruct detailed traffic flow dynamics in both spatial and temporal scopes required for LC studies (LC analysis needs high-precision data to distinguish vehicle movement between adjacent lanes). Arman and Tampère (2022) used data fusion in a four-step method for sufficiently accurate, fully-automated reconstruction of trajectories collected by smartphone GPS to reduce the bias in lateral position to less than half the width of a standard freeway lane. This makes it possible to provide accurate trajectory data in high volume and for long distances.

3.2 Solutions From Empirical Lane Change Studies

Lane change studies analyse where, when, and how drivers change lanes and this evidence, tailored to South African context, can inform targeted interventions like:

- **Infrastructure Design**: Data on lane-changing behaviour can reveal where unsafe lane changes cluster, prompting redesign of such areas. It guides the design of roadways, such as the optimal length of merging lanes (van Beinum et al., 2018) or the placement of signage and markings (Lu et al., 2022). To increase freeway capacity and improve traffic safety, different lane restriction strategies may be considered for heavy vehicles and passenger cars (Moridpour et al., 2010).

- **Traffic Management and Control**: Studying locations of frequent LCs can inform deploying dynamic traffic control measures, like channelization, variable speed limits, adaptive signal timings, ramp metering or combinations of these to regulate vehicles on and (those) entering freeways in weaving sections which are critical bottlenecks (as vehicles merge, diverge, and change lanes frequently) (Deng et al., 2023).

- **Safety Enhancements**: Identifying areas with high incidences of risky lane changes allows for the implementation of safety measures such as lane restrictions, increased targeted enforcement and public safety awareness campaigns.

- **Technology Deployment**: As South Africa explores smart mobility solutions, empirical driver behaviour data (that includes lane changing) is essential for calibrating advanced driver-assistance systems (ADAS) and connected infrastructure (Li et al., 2018).

4. CONCLUSION

Comprehensive lane change behaviour studies are a proven tool for informing road safety and mobility solutions in various countries. For South Africa, investing in such research and making the data readily available would be crucial for designing effective, evidence-based mobility solutions tailored to local realities. By translating driver behavioural insights from existing sources or direct field observations into infrastructure solutions, enforcement strategies, and smart technologies, authorities can improve safety and reduce congestion while fostering equitable access to transport. Therefore, as South Africa continues to urbanize, investing in LC research is not just viable – It is imperative for sustainable mobility.

5. REFERENCES

Ali, Y, Sharma, A & Zheng, Z. 2025. Empirical research on car-following and lane-changing: Recent developments, emerging vehicle technologies' impact, and future research needs. *Transportation Research Interdisciplinary Perspectives,* 31:101368.

Arman, MA & Tampère, CMJ. 2022. Lane-level trajectory reconstruction based on data-fusion. *Transportation Research Part C: Emerging Technologies,* 145:103906.

Ben-Akiva, M, Choudhury, C & Toledo, T. 2006. Lane changing models.

Bham, G. 2011. A simple lane change model for microscopic traffic flow simulation in weaving sections. *Transportation Letters,* 3:231-251.

Bruwer, MM, Behrens, R & Andersen, SJ. 2023. Commercial floating car data application in Sub-Saharan African transport planning contexts: A critical review and research agenda. *Scientific African,* 20:e01692.

Chang, G-L & Kao, Y-M. 1991. An empirical investigation of macroscopic lane-changing characteristics on uncongested multilane freeways. *Transportation Research Part A: General,* 25:375-389.

CSIR. 2025. *The CSIR Transport Safety Laboratory* [Online]. Available at: https://www.csir.co.za/csir-transport-safety-laboratory. Accessed 10 May 2025.

Das, A, Khan, MN & Ahmed, MM. 2020. Detecting lane change maneuvers using SHRP2 naturalistic driving data: A comparative study machine learning techniques. *Accident Analysis & Prevention,* 142:105578.

Deng, D, Yu, B, Xu, D, Chen, Y & Kong, Y. 2023. Automated Traffic State Optimization in the Weaving Area of Urban Expressways by a Reinforcement Learning-Based Cooperative Method of Channelization and Ramp Metering. *Journal of Advanced Transportation,* 2023, 4771946.

Fitch, G, Lee, S, Klauer, S, Hankey, J, Sudweeks, J & Dingus, T. 2009. Analysis of lane-change crashes and near-crashes. *US Department of Transportation, National Highway Traffic Safety Administration*.

Gao, Y & Levinson, D. 2023. Lane changing and congestion are mutually reinforcing? *Communications in Transportation Research,* 3:100101.

Guo, M, Wu, Z & Zhu, H. 2018. Empirical study of lane-changing behavior on three Chinese freeways. *PLOS ONE,* 13:e0191466.

Hess, S, Choudhury, CF, Bliemer, MCJ & Hibberd, D. 2020. Modelling lane changing behaviour in approaches to roadworks: Contrasting and combining driving simulator data with stated choice data. *Transportation Research Part C: Emerging Technologies,* 112:282-294.

Kesting, A, Treiber, M & Helbing, D. 2007. General Lane-Changing Model MOBIL for Car-Following Models. *Transportation Research Record,* 1999:86-94.

Kriel, A. 2017. *Investigating the Sustainability of the Freeway Management System and Feasibility of Implementing a Connected Vehicle Environment in the Western Cape.* Master of Science, Stellenbosch University.

Li, L, Jiang, R, He, Z, Chen, X & Zhou, X. 2020. Trajectory data-based traffic flow studies: A revisit. *Transportation Research Part C: Emerging Technologies,* 114:225-240.

Li, X, Wang, W, Zhang, Z & Rötting, M. 2018. Effects of feature selection on lane-change maneuver recognition: an analysis of naturalistic driving data. *Journal of Intelligent and Connected Vehicles,* 1:85-98.

Liu, X, Hong, L & Lin, Y. 2023. Vehicle Lane Change Models – A Historical Review. *Applied Sciences,* 13:12366.

Lu, Y, Cheng, K, Zhang, Y, Chen, X & Zou, Y. 2022. Analysis of lane-change conflict between cars and trucks at merging section using UAV video data. *arXiv preprint arXiv:2201.07881*.

Ma, C & Li, D. 2023. A review of vehicle lane change research. *Physica A: Statistical Mechanics and its Applications,* 626:129060.

Moridpour, S, Majid, S & Rose, G. 2010. Lane changing models: a critical review. *Transportation Letters,* 2:157-173.

Rahman, M, Chowdhury, M, Xie, Y & He, Y. 2013. Review of microscopic lane-changing models and future research opportunities. *IEEE Transactions on Intelligent Transportation Systems,* 14:1942-1956.

SANRAL 2025. SANRAL's Freeway Management System (FMS). *In:* Sanral (ed.) Available at: https://www.facebook.com/share/v/15SSMqxxqx/. Facebook.

Shawky, M. 2020. Factors Affecting Lane Change Crashes. *IATSS Research,* 44:155-161.

UCT. 2015. *New vehicle simulator (vSIM) to navigate study on effects of brain disorders on driving* [Online]. Available at: https://health.uct.ac.za/articles/2015-10-09-new-vehicle-simulator-navigate-study-effects-brain-disorders-driving. Accessed 9 May 2025.

van Beinum, A, Farah, H, Wegman, F & Hoogendoorn, S. 2018. Driving behaviour at motorway ramps and weaving segments based on empirical trajectory data. *Transportation Research Part C: Emerging Technologies,* 92:426-441.

Vanderschuren, M. 2006. *Intelligent Transport Systems for South Africa: Impact Assessment through Microscopic Simulation in the South African Context.* PhD Thessis, University of Cape Town & University of Twente.

Vechione, M, Balal, E & Cheu, RL. 2018. Comparisons of mandatory and discretionary lane changing behavior on freeways. *International Journal of Transportation Science and Technology,* 7:124-136.

Venter, K. Intertwining road user behaviour and traffic psychology with ITS in South Africa. 2010-05 2010.

Venter, K & Muronga, K. 2016. *Synthesizing Naturalistic Driving Data : A Further Review*.

Wang, W & Cheng, G. 2023. The characteristics of driver lane-changing behaviour in congested road environments. *Transportation Safety and Environment,* 6.

Xie, D-F, Fang, Z-Z, Jia, B & He, Z. 2019. A data-driven lane-changing model based on deep learning. *Transportation Research Part C: Emerging Technologies,* 106:41-60.

Yang, M, Wang, X & Quddus, M. 2019. Examining lane change gap acceptance, duration and impact using naturalistic driving data. *Transportation Research Part C: Emerging Technologies,* 104:317-331.

You, F, Zhang, R, Lie, G, Wang, H, Wen, H & Xu, J. 2015. Trajectory planning and tracking control for autonomous lane change maneuver based on the cooperative vehicle infrastructure system. *Expert Systems with Applications,* 42:5932-5946.

Yuan, R, Abdel-Aty, M, Gu, X, Zheng, O & Xiang, Q. 2023a. A unified modeling framework for lane change intention recognition and vehicle status prediction. *Physica A: Statistical Mechanics and its Applications,* 632:129332.

Yuan, R, Ding, S & Wang, C. 2023b. Comparative Analysis of Machine-Learning Models for Recognizing Lane-Change Intention Using Vehicle Trajectory Data. *Infrastructures,* 8:156.

Zheng, Z. 2014. Recent developments and research needs in modeling lane changing. *Transportation Research Part B: Methodological,* 60:16-32.