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Qualitative and Quantitative Assessment of Public Minibus Taxi Driving

Nomfundo Cele · Alain Kibangou · Walter Musakwa

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Abstract In most developing countries, a significant percentage of households rely on public transport, specifically informal minibus taxis. In South Africa, this mode of transport is more regularly involved in road traffic accidents compared to other modes. However, very few studies have focused on analyzing driving in this transportation mode from the perception of the commuter. In this study, the analysis is carried out using qualitative (questionnaires) and quantitative (speed and acceleration) data with the aim of finding factors that characterize public transportation drivers, specifically understanding how minibus taxi drivers differ from other drivers and how the regulatory environment influences their on-road behavior. The personality and skills of the drivers are shown to be the two main factors to analyze. It is shown that minibus taxi drivers perform lower than ride-hailing drivers. In addition, their driving is more aggressive in a controlled environment, while it is more reckless in an uncontrolled environment. Cultural, training, and technology-oriented actions are suggested to improve the on-road driving of the minibus taxi in the chosen study area.

Keywords : Public Transport · Minibus Taxi · Driving Quality · South Africa

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1 Introduction

Road accidents are one of the six highest causes of disability and kill over 1.35 million people each year; more than tuberculosis, diarrheal diseases, or HIV/AIDS [39,28]. Each year nearly 50 million commuters are injured or disabled by traffic accidents [40]. The majority of these fatalities occur in developing countries, transforming road accident mortality into both a socioeconomic development challenge and a public health concern [14]. This issue is exacerbated by the rapid pace of motorization and urbanization [33]. That is why the United Nations incorporated road safety into sustainable development goals (SDGs), in particular in SDG 3 on good health and well-being and SDG 11 on sustainable cities and communities [36]. The persistence and extent of this public health issue demands new methods to road safety procedures [27].

Due to the announced 2021-2030 Decade of Action for Road Safety by the World Health Organization (WHO), road safety has become a major area of interest for researchers, policy makers and transport engineers [31]. Research conducted by public institutions, private entities and scholars, such as [13], on traffic safety discovered that human error was a contributing factor in over 90% of road-traffic accidents while only 2.4% were caused by mechanical problems and 4.7% by environmental issues alone [13]. Identified contributing factors include unsafe driving behaviors (speeding, reckless driving, and drug or alcohol), road curves, undulating terrain and driver distraction [3].

In South Africa, the WHO reported that the country's cities are particularly prone to traffic accidents, with approximately one million road-traffic incidents occurring annually. According to the Road Traffic Management Corporation, fatal accidents claim the lives of over 40 people daily, while at least 20 others suffer lifelong injuries resulting in permanent disability due to road-traffic collisions [39]. It is

worth noting that in South Africa 75% percent of households depend on public transport, the minibus taxi having the greatest modal share [32][26]. This mode plays a significant role in the lives of South Africans but, when it comes to research, minimum attention has been given to driving behavior concerns, working conditions, and the attitude of law enforcement toward these drivers. The country faces a road-traffic accident mortality rate that is over double the international average, and well over the African region average [18]. Minibus taxis are more regularly involved in road-traffic accidents compared to other modes. Each year, minibus taxis account for 70,000 road-traffic accidents; the double of the number of other public transport modes with higher deadly crash rates (projected at approximately 20 per 100 million vehicle km traveled) than freight vehicles and buses (10 per 100 million vehicle km) [30]. Speeding is responsible for nearly 40 percent of fatal crashes as a result of human error [1]. In [7], it was found out that median width, vehicle speed, road width, and access roads impact the incidence of road-traffic crashes, while in [35] a neighborhood measure of crime and violence indicated to be a notable predictor of road-traffic fatalities in addition to several factors linked to driver behavior, socio-economic deprivation, and traffic exposure. The strong link of driver behavior with road traffic crashes was also highlighted by [2] and [21].

Literature review by [43] stated that driver behavior and driving style (the way a driver operates his vehicle and the behavior he displays while driving) fall into two classes of studies: vehicle motion research and survey studies. The later uses self-reported questionnaires on driving habits to investigate relations between driver personality, driver behavior and driving style factors [9,17,37,41]. Vehicle motion research collect and use data on the movement of the motor vehicle to categorize the driving style of vehicle drivers. These studies usually classify driving style in three groups: aggressive, normal, and calm [11,16,22]. Harsh deceleration and acceleration, high speeds, harsh vertical and lateral movements, sudden changes in motor steering angles are usually related with aggressive driving behavior [38]. A calm driving style is characterized by controlled deceleration, lower speeds, gradual acceleration, controlled longitudinal maneuvers, smooth lateral movements, and minimal adjustments to the steering [4,38]. Various algorithms and methods can be used to classify driving styles and the two main categories are rule-based approaches and machine-learning based approaches. Taking into consideration the challenges in acquiring driver style classifications in real application settings, current studies mainly employs unsupervised learning algorithms to detect and categorize driving styles. Random forest decision methods, support vector machine, and artificial neural networks are often the most utilized methods for the categorization of driving style [5,16,23,43].

In the literature, driving is analyzed by questioning drivers or by recording data from on-board sensors, which requires equipping the vehicle with specific sensors. Noting that very few studies have focused on the quality of road driving of minibus taxi drivers, despite the fact that it is a major mode of transport in developing countries and is involved in a significant number of accidents. In this article, we adopt the point of view of the passenger, who is the beneficiary of the service and unfortunately the potential victim of poorly controlled driving. Knowing the significant role played by minibus taxis in public transport in developing countries, from the passengers point of view, the research questions we would like to address are as follows:

- what factors characterize the drivers of the different modes of transport used by the majority of passengers in the case study? (Q1)
- how do minibus taxi drivers differ from other drivers with regard to these factors? (Q2)
- how does the regulatory environment influence the on-road behavior of minibus taxi drivers? (Q3)

The proposed analysis is based on qualitative and quantitative data. Qualitative data was obtained by means of questionnaires, where a sample of commuters were asked to evaluate various attributes of three transportation modes (minibus taxi, bus, and ride hailing) related to the driver. Quantitative data was obtained using a smartphone carried by a passenger in two contexts: controlled environment with high visibility law reinforcement and uncontrolled environment where drivers face only their consciousness to follow rules or not.

The paper is organized as follows. Section 2 concerns the study context, data and the methodology. Results are presented and analyzed in Section 3. Lastly a discussion and policy implications are provided in Section 4 before concluding the paper.

2 Study context, data and methods

2.1 Study context

The study considers a township named KwaDabeka Ward 20, a disadvantaged area located 25 kilometers west of Durban's Central Business District (CBD) in KwaZulu Natal Province of South Africa. This township has a population of 28,853; almost 19,042 adults (18 years old and above). It is mostly inhabited by blacks, unemployed, and low income earners. The area is mostly residential with little economic or industrial activity. Given the socioeconomic background of the area, it is necessary to travel to Durban CBD and other places of interest for work, health, education, and entertainment. This can be done using minibus taxi, bus, train, and ride hailing services. However, the township is dominated by the minibus taxi industry, and has proven to be one of the

greatest challenges in public transportation in KwaDabeka. The minibus taxi routes in this area, from this township to the main places of activity, lacks a visible presence of law enforcement entities.

2.2 Data

2.2.1 Qualitative data

The questionnaire used in this study was designed to be concise and targeted, consisting of demographic questions (age, gender, employment, and level of education) followed by a single core question: "Rate, from 1 to 10, your level of satisfaction according to the following attributes (see the list in Appendix 1)". The questionnaire was set up following the steps below:

1. Design process: The question and satisfaction attributes were developed based on a review of the literature on user satisfaction in mobility studies. The attributes reflect key dimensions commonly evaluated in transport satisfaction research.
2. Validation process: The questionnaire was internally reviewed and approved by senior co-authors who are experts in both engineering and social sciences with a strong focus on mobility issues. Their interdisciplinary expertise ensured the relevance and clarity of the attributes included.
3. Pilot testing: A pilot test was conducted with a small group of 10 participants to verify that the attributes were easily understood and that the single satisfaction question was clear. Feedback from the pilot test confirmed the interpretability of the questionnaire.

Given the focused and straightforward nature of the questionnaire, we did not conduct formal quantitative reliability testing. However, the rigorous design process, expert review, and pilot testing ensured that the question and attributes properly capture the intended subjective data.

Pen-and-Pencil Interview (PAPI)/Face to face interview was used for the survey purpose. The researcher explained the purpose of the study and the definitions of the considered attributes to each respondent. The researcher made sure the questions were properly understood by using the local language if necessary. Evaluation was carried out for different transportation modes (Minibus taxis, ride-hailing (Uber), Bus, and train (metrorail)). In this paper, the focus is on the attributes defined in Table 1 and for road transportation modes (minibus taxi, bus, and ride-hailing).

The data was collected over a period of 2 months (30 September to 2 December 2022). The study did not include minors. The sample size is 240. It is found to be adequate (> 194) for a population of 19,042 at a 95% confidence level, 7% margin error, and worst-case percentage of 50%

[34]. A random sampling method was adopted to conduct the survey while targeting a gender balance among a population that uniquely uses public transportation to access places of employment, and other services such as health care and shopping centers. The socio-demographic information of the respondents is given in Table 2. The study adhered to the ethical procedures of informed consent, voluntary participation, honesty, confidentiality and anonymity. The study required ethical clearance and it was granted on the 19th of August 2021 by the University of Johannesburg ethics committee.

2.2.2 Quantitative data

Over a period of 2 months (September and October 2023), a single researcher carried out data collection as a passenger of a minibus taxis. The same Android smartphone, placed in a handbag carried on the lap, was used to collect GPS data. Knowing that the inertial movement of either the researcher or the handbag could potentially introduce bias into the collected GPS data, the following measures were taken:

1. Stable positioning of the smartphone: the smartphone was firmly placed inside a fixed compartment of the handbag, reducing internal movement of the device.
2. Minimizing human movement: the handbag was kept stable on the user's lap throughout the journey without any handling. The absence of significant movement was verified during preliminary trials.
3. Consistency of GPS data: the GPS readings, collected using the Senslogs App, were evaluated to detect any irregularities such as position jumps or abnormal shifts, and only stable data were retained for analysis. Some recordings were discarded and 77 were considered as consistent.

These precautions ensure that the smartphone's GPS sensor can reasonably be considered as being attached to the vehicle, thereby minimizing potential biases. Based on interviews conducted with minibus taxis unions during the data collection phase, it appears that nearly 900 minibus taxis are registered in KwaDabeka. For this number, 77 trips is adequate (> 63) at a 90% confidence level, 10% of margin error, and worst-case percentage of 50%. The minibus taxis were randomly selected, without repetition, and drivers were uninformed of the data collection campaign to avoid cognitive biases. The research did not require drivers participation or responses and did not interact with the drivers. The research used 50 recorded trips in a controlled urban area, a 2.5 km route stretched from Marine Parade to Suncoast Casino. This route has high visibility of metro police, metro police station, speed bumps, traffic robots (traffic lights), roundabouts, and traffic circles as measures to control driver behavior on the road. The research used 27 recorded trips in an 8.4 km uncontrolled route stretched from KwaDabeka to

Table 1 Evaluated attributes of the considered public transportation system.

Index	Name	Interpretation
1	Politeness	Friendly attitude towards commuters (e.g. greetings, respect,...)
2	Safety	Exposure to criminal activities, theft, harassment at stations and during transit
3	Driving style	The way a driver operates his vehicle and the behaviour he displays while driving including compliance to road traffic regulation
4	Waiting time	Time spent before departure
5	Speed	Driving in high speed

Table 2 Demographics information

Total number of respondents: 240		
Gender	Male	50%
	Female	50%
Age	Under 25	22%
	26-33	28%
	34-41	29%
	Above 41	21%

Pinetown. It has traffic robots and speed bumps as measures to control driver behavior on the road. The smartphone data is based on GPS measurements, precisely location x_t and speed $v(x_t)$, on the minibus taxis. The location is used to confirm whether the route used by the minibus taxi is an urban road where the speed is limited to 60km/h or an expressway where the speed is limited to 100km/h for this category of vehicles. The speed is normalized as

$$\bar{v}_t = \frac{v(x_t)}{V(x_t)} \quad (1)$$

where $V(x_t)$ stands for the speed limit at location x_t . This normalization step allows to detect over-speeding whatever the speed limitation. Since the GPS data was recorded at a 1Hz frequency, acceleration is computed as

$$a_t = v(x_t) - v(x_{t-1}) \quad (2)$$

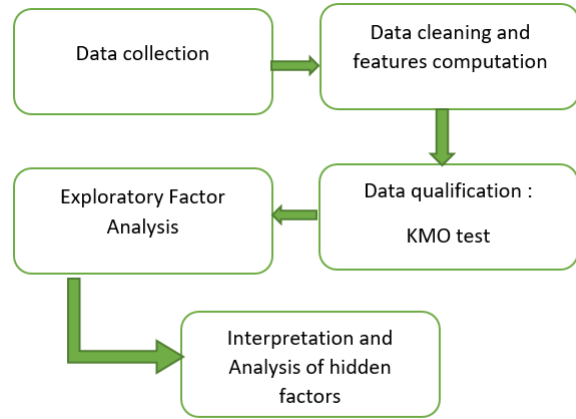
for each time sample t .

2.3 Method

Whether using data from questionnaires (qualitative data) or from GPS (quantitative data), the considered method is based on the following steps (see Fig. 1): (i) data collection, (ii) data cleaning and features computation, (iii) data qualification, (iv) Exploratory Factor analysis, and (v) interpretation and analysis of hidden factors.

Consider $\mathbf{S} \in \mathbb{R}^{N \times K}$ a data matrix to be analyzed, where N and K stand for the number of records and the number of evaluated attributes respectively. The entry $s_{n,k}$ of \mathbf{S} stands for the evaluation of the k th attribute in the n th record. The principle of Explanatory Factor Analysis (EFA) [15] is to model \mathbf{S} as

$$\mathbf{S} = \mathbf{A} + \mathbf{L}\mathbf{F}^T + \mathbf{E} \quad (3)$$

**Fig. 1** Methodology.

where $\mathbf{A} \in \mathbb{R}^{N \times K}$ contains the observation means of each attribute, $\mathbf{L} \in \mathbb{R}^{N \times R}$ stands for the loadings matrix, $\mathbf{F} \in \mathbb{R}^{K \times R}$ the hidden factors matrix, and $\mathbf{E} \in \mathbb{R}^{N \times K}$ the error term matrix. R denotes the number of hidden factors, which can be estimated using a scree plot and/or the explained variance. Our objective is to find \mathbf{F} . It is generally obtained by solving a maximum likelihood problem. In this study we used Matlab to solve the EFA problem. However, prior to applying an EFA, it is important to evaluate the suitability of data. The Kaiser-Meyer-Olkin test (KMO) can be used to evaluate the suitability of the data for EFA. The statistic is a measure of the proportion of variance among variables that might be common variance. The higher the proportion, the higher the KMO-value, the more suited the data to factor analysis. Kaiser proposed that a KMO value greater than 0.9 was marvelous, in the 0.80s, meritorious, in the 0.70s, middling [19]. In the literature, a KMO value greater than 0.7 is considered as acceptable [29].

Interpretation of the obtained factors can be deduced by analyzing the attributes that contribute the most to the considered factor, i.e. values $f_{k,r}$ of \mathbf{F} .

Then we can compute the score $w_{n,r}$ of the n th record on the r th hidden factor as follows

$$w_{n,r} = \frac{\sum_{k=1}^F s_{n,k} f_{k,r}}{\sum_{q=1}^F f_{q,r}} \quad (4)$$

2.3.1 Method for the assessment of minibus taxi drivers with regards to other modes

Here the data matrix $\mathbf{S} \in \mathbb{R}^{N \times K}$ contains the records of the $N = 3 \times 240$ evaluations of the 3 considered modes by the 240 respondents of the questionnaire about the $K = 5$ attributes listed in Tab. 1. For the analyzed set of data, we got a KMO = 0.747. We can therefore perform EFA on this data. After computing the eigenvalues of the correlation matrix, the scree plot depicted in Fig. 2 allows us to select 2 hidden factors. The Pareto curve on Fig. 3 confirms that almost 70% of the variance is explained by the two first factors. We therefore conclude that the observed attributes are related to two hidden factors. Given \mathbf{F} obtained by perform-

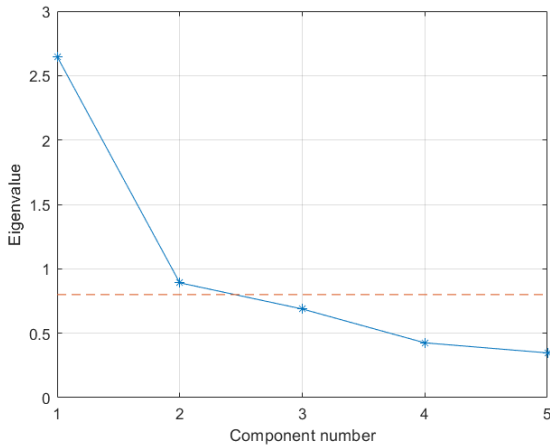


Fig. 2 Scree plot for the analysis of qualitative data.

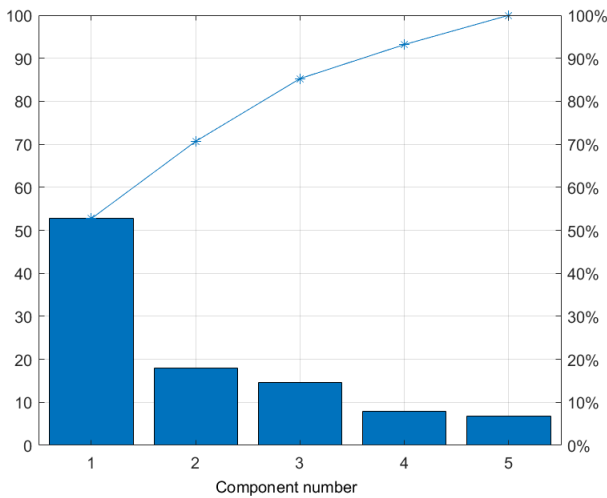


Fig. 3 Explained variance of qualitative data: individual (bar) and cumulative (solid line).

ing EFA on \mathbf{S} using Matlab, we can deduce the scores $w_{n,r}$, $n = 1, 2, \dots, N$, $r = 1, 2$. By grouping $w_{n,r}$ according to the corresponding transportation mode, statistics of each hidden factor can be computed for each transportation mode to compare these modes. This is done in section 3.1.

2.3.2 Method for the assessment of minibus taxi drivers with regards to the regulatory environment

As stated in section 2.2.2, we have $N = 77$ records of speed and location of minibus taxis in both controlled and uncontrolled environment. From the speed we can deduce acceleration (see equation (2)). If $a_t > 0$ the vehicle is accelerating while $a_t < 0$ accounts for deceleration. According to the literature [12,20], acceleration or deceleration is considered as risky if $|a_t| > 1.2$ ms. In the sequel we will count the ratio of such events as a marker of risky driving:

$$R_a = \frac{\sum_{t=1}^T H(a_t - 1.2)}{\sum_{t=1}^T H(a_t)}, \quad R_d = \frac{\sum_{t=1}^T H(-a_t - 1.2)}{\sum_{t=1}^T H(-a_t)} \quad (5)$$

where R_a , R_d , and $H(\cdot)$ stand for the ratio of risky events during acceleration, ratio of risky events during deceleration, and the Heaviside step function, respectively. In this study, we also consider the stopping distance as an attribute to be evaluated. The stopping distance is the distance needed to stop the car. It is the sum of the reaction distance with the deceleration distance

$$SD_t = v(x_t)T_r + \frac{v^2(x_t)}{|a_t|} \quad (6)$$

in deceleration mode where $T_r = 0.68s$ stands for the reaction time. The proof is provided in the appendix. In the sequel The stopping distance is normalized by 70m considered as a good compromise when considering the maximum speed in both controlled and uncontrolled areas. For the analysis, as attributes, we consider the risky acceleration ratio, the risky deceleration ratio, the maximum normalized speed, and some statistics of the normalized speed, the acceleration, the deceleration, and the stopping distance; precisely, the 10th, 50th (median), and 80th percentiles. The attributes allowing higher data suitability for factor analysis according to the KMO are given in Table 3. Note that the 10th percentile of the normalized speed and of stopping distance were discarded since they lowered data suitability for factor analysis. Therefore the data matrix \mathbf{S} to be analyzed is 77×13 . We got KMO=0.8062 meaning data is meritorious for factor analysis. When performing the scree-plot, we also get a number of hidden factors $R = 2$. Therefore, given \mathbf{F} obtained by performing EFA on \mathbf{S} using Matlab, we can deduce the scores $w_{n,r}$, $n = 1, 2, \dots, N$, $r = 1, 2$. By

Table 3 Selected features and their weights.

Number	Definition	Factor 1	Factor 2
1	Maximum normalized speed	0	0.530
2	Median of normalized speed	0	0.710
3	80th percentile of normalized speed	0	0.900
4	Risky acceleration ratio	0.689	0
5	10th percentile of acceleration	0.7491	0
6	Median acceleration	0.859	0
7	80th percentile of acceleration	0.785	0
8	Risky deceleration ratio	0.964	0
9	10th percentile of deceleration	0.613	0
10	Median deceleration	0.896	0
11	80th percentile of deceleration	0.979	0
12	Median stopping distance	0	0.763
13	80th percentile of stopping distance	0	0.696

grouping $w_{n,r}$ according to the corresponding regulatory environment, statistics of each hidden factor can be computed for each environment for comparison purpose. This is done in section 3.2.

3 Results

3.1 Assessment of minibus taxi drivers with regards to other modes

After applying EFA, we get the loadings $f_{k,r}$ of the two hidden factors given in Table 4.

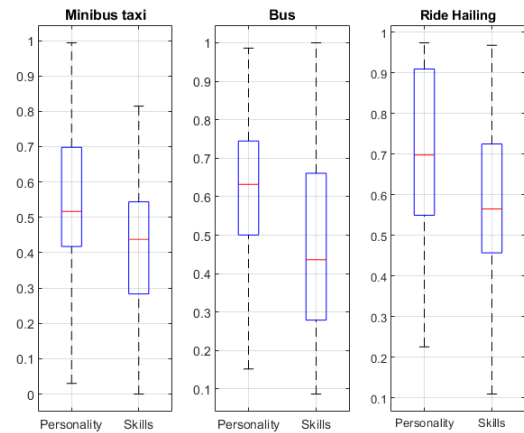
Table 4 Loadings of identified factors.

	Factor 1	Factor 2
Politeness	0.896	-0.173
Safety	0.764	-0.073
Driving style	0.383	0.381
Waiting time	0.203	0.378
Speed	-0.178	1.101

By adopting a threshold of 0.3 (values highlighted in bold in Tab. 4), one can note that the first factor is more related to Politeness, Safety, and Driving style while the second factor is related to Speed, Driving style, and Waiting time. Therefore one can interpret Factor 1 as related to the driver's personality while the Factor 2 is related to the driver's skills. It can be noticed that the driving style depends on both personality and skills. Note that it is, at first glance, surprising to link waiting time to driver skills. However, by considering in details the way these transportation modes operate, the waiting time is a consequence of an optimization the driver needs to carry out. Waiting time is the time spent prior departure. This could be at the bus stop, stop, minibus taxi rank or pick-up location for ride hailing. For example, for minibus taxis, commuters egress at the taxi

rank to board the respective minibus taxis. Sometimes commuters wait in a queue to board a minibus taxi or commuters wait in the minibus taxi for it to be filled to capacity. The driver has to optimize the profit. Optimizing one ride would mean waiting until full capacity is reached while optimizing the daily profit can lead to shorten the waiting time and maximize the number of rides. To do so efficiently the driver must be skilled enough.

Given $f_{k,r}$, we can deduce the scores $w_{n,r}$, as given by equation (4) and then perform the analysis per mode. The obtained scores are normalized to a range of 0 to 1 for comparison. The results are depicted in Fig. 4.

**Fig. 4** Factor scores for each mode.

At first glance, it can be observed that regardless of the mode, the driver's personality is better evaluated than their skills. To ensure that this difference is significant, we conducted a t-test with the null hypothesis stating no difference in the average evaluation of the driver's personality and competence. As it can be seen in Table 5, considering the standard threshold of 5%, the null hypothesis is rejected for collective transportation modes (minibus taxi and bus), not for ride hailing. This means the difference in the evaluation of drivers' personality and skills is significant for collective transportation modes. A second observation is about differ-

Table 5 Significance of the difference in the evaluation of the personality and the skills of the drivers.

	Minibus taxi	Bus	Ride hailing
P-value	0.031	0.021	0.207

ence between collective transportation modes and ride hailing. To test its significance, we resort again to a t-test with null hypothesis drivers personality (resp. skills) are in average the same as for minibus taxi. It can be seen in Table 6 that the null hypothesis is rejected in the case of ride hailing.

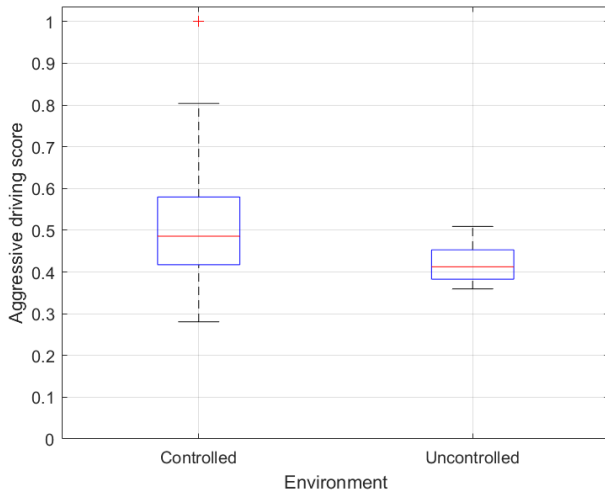
Table 6 Significance of the difference in the evaluation of drivers' personality and skills according to transportation modes.

	Bus	Ride hailing
P-value for driver's personality	0.112	0.018
P-value for driver's skills	0.237	0.002

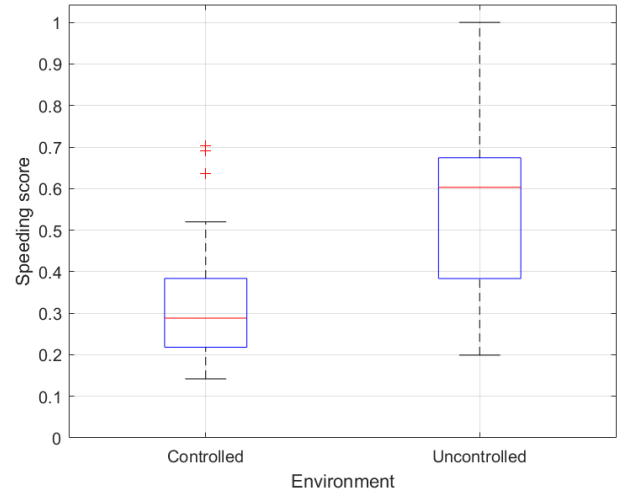
Since evaluation is higher for ride hailing, the significance difference points out that drivers' skills seem being a major concerns for collective transportation modes than for ride hailing.

3.2 Assessment of minibus taxi drivers with regards to the regulatory environment

Using the scree plot criterion, two factors can explain the collected data. To interpret these factors, we set a threshold of 0.5 to the obtained coefficients. After thresholding we get the results in Table 3. It can be noticed that the first factor is related to acceleration and deceleration. It accounts for driving aggressiveness. The second factor is constituted with features related to speed and stopping distance; it accounts for speeding. Similarly to the analysis carried out in section 3.1, we can compute the scores $w_{n,r}$ and then perform the analysis by regulatory environment. Figure 5 (resp.

**Fig. 5** Statistical distribution of the aggressive driving score.

6) depicts the statistical distribution of the aggressive driving (resp. speeding) score. We observe that aggressive driving is more prevalent in a controlled environment, whereas speeding is more prominent in an uncontrolled environment. The significance of the difference is confirmed by p-values given in Table 7. The above results indicate that the driving style of minibus taxi drivers is more aggressive in controlled environments where there is a high number of speed

**Fig. 6** Statistical distribution of the speeding score.**Table 7** Significance of the difference between environments.

	Aggressive driving	Speeding
P-value	0.003	4.685×10^{-9}

bumps, roundabouts, traffic circles, and traffic robots. The results on the speeding score show that high visibility of metro police, speed bumps, roundabouts, traffic circles, and traffic robots reduces speeding unlike in uncontrolled environments which have traffic robots and a few speed bumps to reduce at-risk driving. One can conclude two opposite behaviors with respect to the level of presence of law enforcement: aggressive in controlled environment and speeding in uncontrolled one.

4 Discussion and policy implications

Based on the results above, we propose a three-fold action plan to address drivers' personality and skills, as well as the aggressiveness and speeding of their driving, which may also be influenced by contextual factors such as the visibility of law enforcement.

4.1 Cultural actions

Driver personality is shaped by culture, and improving it can be achieved through cultural workshops or campaigns that promote community engagement with public transport drivers. These initiatives should focus on the concept of Ubuntu, emphasizing that an authentic individual is part of a broader relational, communal, and spiritual world [25]. Furthermore, a review by [24] highlights how Zulu people use impression management strategies to positively influence perceptions

in work environments, including transport services. Impression management shapes how individuals perceive and engage with their surroundings, fostering favorable impressions and encouraging positive interactions.

4.2 Training actions

Programs promoted by the municipality [10] include identifying champions and volunteers, promoting road safety, reducing drunk driving, encouraging seat belt use, addressing speeding, and raising awareness of road rules. Increased visibility of police, especially in towns, has educational potential. The Road Safety Action Plan emphasizes the importance of driver attitudes and the municipality's role in speeding up planning and implementation. Aligned with the Decade of Action for Road Safety in Africa, deterrence theory suggests that penalties outweigh the benefits of unlawful driving behavior [2, 6]. This theory supports traditional practices such as awareness campaigns, workshops, and seminars. Effective measures require drivers to understand the high likelihood of detection, swift penalties, and harsh punishments. Workshops for minibus taxi drivers are crucial to improving professionalism, reducing dangerous driving, and enhancing service quality.

4.3 Technological actions

In addition to cultural and training efforts, technology-driven solutions are essential. Public institutions should increase funding for road safety research, while government and transport agencies invest in intelligent transport systems (ITS) to reduce accidents. ITS integrates computers, communications, and technologies to create an integrated system of roads, vehicles, and people. Research should focus on leveraging big data and AI to enhance public transportation, improve driver behavior analysis, and optimize planning [42]. The use of technologies like GPS, Wi-Fi, and sensors in smartphones can improve traffic safety and public transit quality by monitoring travel and driver behaviors [8]. The municipality road safety mentions on plans to have fixed and mobile cameras to enforce speed limits [10]. There are plans to have software and devices to monitor drivers speeding. It is suggested that the municipality does not only plan for the urban areas but include the township areas. In KwaDabeka there are no speed cameras to ensure that drivers adhere to the speed rules even on the freeway. As much as the city is proposing and planning to provide some type of transportation technologies, it would be suggested to involve the public by way of encouraging, supporting, and financing feasible external transportation technology solutions. It is suggested to include this in the eThekweni Municipality road safety action plan, to encourage think tanks through funding

opportunities. To plan for programs such as business incubation programs for exclusively transport technology businesses within the municipality. It requires all stakeholders in the road public transport sector to work together to provide effective solutions.

5 Conclusion

The quality of driving in the informal public transport sector is a key issue, given that a significant percentage of commuters in developing countries depend on these means of transport. However, very few studies have been dedicated to this topic. By considering a township in South Africa in KwaZulu-Natal as a case study, this paper has provided a contribution on concocting tools to identify the key factors to improve commuter safety in similar areas. One of the original features of this paper is that it considers the commuter's point of view rather than that of the drivers. Indeed, the study is based on qualitative data based on questionnaires from commuters and quantitative data obtained from a smartphone carried by a passenger. From qualitative data, the study shows that the quality of driving can be characterized by two factors: the driver's personality and the driver's skills. A deeper investigation using quantitative data on driving style of minibus taxi drivers further allowed us to identify two hidden factors: driving aggressiveness and speeding. These factors are expressed differently in controlled and uncontrolled environments. It is probable that driver personality and skills are related to driving aggressiveness and speed but require further investigation. Another future work concerns ways to mitigate road-crash fatalities in low- and middle-income countries. Very little research has been done on the solution to this critical issue on the African continent. Suggestions have been provided that include cultural, training and technological actions.

Abbreviations

EFA: Explanatory Factor Analysis;
GPS: Global Positioning System;
KMO: Kaiser-Meyer-Olkin;
SDG: Sustainable Development Goals

Appendix

Appendix 1: Questionnaire

See Fig. 7

Appendix 2: Stopping distance

Assume that the driver sees an obstacle while he is driving at speed $v(x_t)$. A reaction T_r is needed before starting brak-

Questionnaire N°:

Age: Under 18 18-25 26-33 34-41 42-49 50-57 58-65 Above 65

Gender: Male Female Other

Education: None Primary Matriculated Certificate Diploma Degree Postgraduate

Rate from 1 to 10 your level of satisfaction (10 being the highest score)

	Overall score	Politeness	Safety	Travel-time	Waiting time	Speed	Driving style	Affordability	Accessibility to the stop (Bus stop/station, taxi rank/stop, train station or pick-up place)	Quality of infrastructure (Bus stop/station, taxi rank/stop, train station or pick-up place)
Taxi										
Bus										
Uber										
Metrorail										

Fig. 7 Questionnaire

ing. Therefore, he has moved a distance $v(x_t)T_r$. Let v_f be final speed after starting braking. From basics kinematics it can be shown that $v_f^2 = v^2(x_t) + 2a_t\Delta x$, Δx being the distance traveled. When the vehicle stops, $v_f = 0$, therefore $\Delta x = -\frac{v^2(x_t)}{2a_t}$. Since we are in deceleration mode, $a_t < 0$. As a consequence, $\Delta x = \frac{v^2(x_t)}{2|a_t|}$. One can then deduce the stopping distance as $v(x_t)T_r + \frac{v^2(x_t)}{2|a_t|}$.

Declarations

The authors declare that this research is their own work.

Ethics Approval and Consent to Participate

The study required ethical clearance and it was granted on the 19th of August 2021 by the University of Johannesburg ethics committee. Ethical clearance number: UJ-FEBE-FEPC-00290. The study adhered to the ethical procedures of informed consent, voluntary participation, harm and risk, honesty, and trust, confidentiality, and anonymity.

Consent for Publication

Not applicable.

Availability of data and materials

Data and materials are available upon request.

Competing Interests

The authors declare that they have no conflict of interest.

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Authors' Contributions

N.C.: Data collection, writing

A.K.: Conceptualization, data analysis, writing, supervision, funding.

W.M.: Supervision, writing–review and editing, and project administration.

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